AUTOMATED SEGMENTATION OF LIDAR POINT CLOUDS FOR BUILDING ROOFTOP EXTRACTION

Yi Sun[1, 2],
Cheng Wang[1],
Jonathan Li[1, 3],
Zongliang Zhang[1],
Dawei Zai[1],
Pengdi Huang[1],
Chenglu Wen[1]

[1]Fujian Key Laboratory of Sensing and Computing for Smart Cities, Xiamen University, Xiamen, FJ 361005, China
[2]Xizang Key Laboratory of Optical Information Processing and Visualization Technology, Xizang Minzu University, Xianyang, SN 712082, China
[3]GeoSTARS Lab, Department of Geography and Environmental Management, University of Waterloo, Waterloo, ON N2L 3G1, Canada

ABSTRACT

LIDAR (Light Detection and Ranging) is an especially effective tool for acquiring geo-referenced point clouds of urban site. Accurate extraction of elevated features such as building rooftops is vitally important in various applications. However, it is still challenging to determine an accurate rooftop contour from the irregularly distributed LIDAR point clouds. In this paper an efficient LIDAR segmentation method is presented in order to achieve automated rooftop extraction. First, we apply a voxel-based upward growing algorithm that filters out the ground points from the raw point cloud scenes. Second, we employ a Euclidean based clustering method on non-ground points by making use of nearest neighbors. Then we introduce RANSAC (RANdom SAmple Consensus) technique to estimate primitive planes for fitting rooftop facets. Finally, we use concave hull and L_0 regularization to determine the rooftop contour. Accurate experimental results demonstrate the validity of our segmentation method for rooftop extraction.

***Index Terms*—**LIDAR, Segmentation, Point Cloud, Building, Rooftop Extraction.

1. INTRODUCTION

Current LIDAR systems can acquire high spatial resolution point cloud data rapidly with an unprecedented level of details of urban environments. LIDAR point cloud is a significant information for numerous applications, including urban planning, topographic mapping etc. [1], [2]. Elevated features identification is often required in such applications. Extraction of such features as building rooftops is a main process in urban planning [3]. Hence, many segmentation approaches have been developed by several researchers. These approaches can be categorized into three main area: model-based fitting [4], [5], morphological filtering [6], [7], and supervised learning method [8].

The model-based fitting approach has been employed to segment the building rooftop by making use of the rooftop topology structure. Reference [4] determines the clusters with fuzzy k-means algorithm for roof segments. It updates the topologic weights of each cluster center iteratively, and then assigns each data point to its closest center. Reference [5] employs a region-growing algorithm to extract roof planes from non-ground LIDAR point cloud. It presents a rule-based method as well to remove false planes.

In case of knowing the location of a building beforehand, the Morphological filtering approach can be employed. Reference [6] performs morphological operations with increased window sizes to separate non-ground objects from terrain features. Reference [7] determines multiple roof segments simultaneously with the method of multiphase and multichannel level set. It separates the coplanar roof segments from parallel roof segments by analyzing their connectivity and homogeneity.

Research on supervised learning method takes advantage of specified training features to achieve high precision segmentation results. Reference [8] adapts SVM (Support Vector Machine) and local descriptors to classify the non-ground point clouds with geometrical and contextual features, respectively.

In this paper, we focus on utilizing a set of algorithms to generate more accurate results for fully-automated rooftop extraction. The remainder of this paper is organized as follows. Section 2 presents the overall approach in detail. Section 3 provides and analyzes the experimental results to demonstrate the effectiveness of the proposed method, and Section 4 draws a conclusion.

2. METHOD

Fig. 1 shows the flowchart of the proposed method. The method consists of five major steps. Firstly, we separate the ground points from the non-ground points (also called as object points) via a voxel-based upward growing algorithm. Only the non-ground points are preserved since the method focuses on building rooftop extraction. Secondly, we divide the object points into different clusters using Euclidean distance as the metric. Thirdly, we estimate the rooftop facets by utilizing RANSAC, with the assumption that the geometric model is planar. Then we discriminate the spatial relation between the facets, upon which the rooftop structure can be derived. Finally the procedure branches into one of two results; we either extract the contour for a flat rooftop or a shed rooftop, or we extract intersection edge, rooftop contour and surfaces for a gabled rooftop or a complicated structured rooftop.

2.1. Ground filtering

Ground filtering is a preparative step for classifying the non-ground points into different objects. Therefore, a variety of approaches are implemented in literature to split the point cloud into ground points and object points [9] [10]. In our proposed method, we implement a voxel-based upward growing algorithm to remove the ground points [11]. At first, the entire scene is divided into a series of local points block vertically on the XY plane to reduce the time and space complexity. Then each block is subdivided into spatially continuous voxels according to the octree index structure. After that, calculate the global elevation and local elevation in the block for each voxel. The voxel elevation along with the elevation threshold is used to filter out the ground points. This voxel-based ground filtering algorithm is chosen due to its speediness, effective process of scenes with strong fluctuations, and its ability to retain the integrality of object points.

2.2. Euclidean based clustering

The filtered object points are still irregularly distributed. It's rather difficult to extract accurate rooftop facets from the point clouds directly. The points need to be grouped into clusters in terms of the spatial context. Thus we choose Euclidean distance clustering method to group points into different clusters. This step begins with changing the coordinates of each point into the offset value, for the sake of decreasing the computational complexity. A Kd-tree repr-

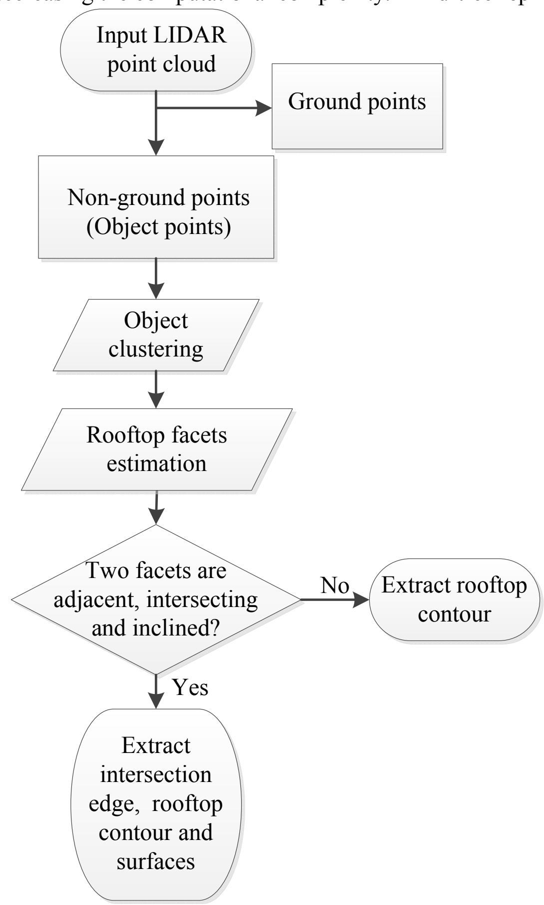


Fig. 1. The flowchart of the proposed method.

esentation is created for each point p_i in the point cloud. The neighbors P_k^i of point p_i are searched with a radius threshold based on Euclidean distance, and then assign P_k^i to the cluster including p_i. The algorithm terminates after each p_i has been processed.

2.3. Facets estimation

Prior to this point, the input for processing procedure is data points. Now processing each individual cluster is the major task. We apply RANSAC to fit the initial rooftop facets from the individual point sets suppose that the rooftop facets are planar. Start with selecting a random point set and apriori inliers to fit a plane, then test the remaining data and determine the points belonging to this plane based on a pre-specified distance threshold. Afterwards the inliers are estimated from the data iteratively. In each iteration the new result replaces the last one if it outperforms the old one. The point set of the saved plane are selected as a rooftop facet eventually. The fitting results are robust to the input data which even contain significant outliers thanks to the plane parameters that is estimated only from the inliers.

2.4. Spatial relation identification of facets

Once the rooftop facets are extracted, we identify the spatial relation of all facets so as to define the rooftop outline appropriately. Firstly we determine whether the rooftop facet is horizontal according to its normal vector. Next for those inclined facets, we analyze the spatial relation among them. We denote each facet by Ω_i and its corresponding point sets by P_i. For a given Ω_A, calculate the distance d_A between point $p_A \in P_A$ and any facet Ω_B in the point cloud with a kd-tree. The process is also repeated for all points in P_B with Ω_A to generate d_B. We seek the minimum value in all d_A and d_B, respectively. Facets are considered adjacent if the values are both smaller than a preset threshold. Furthermore, two adjacent facets are considered intersecting if the angle difference of their normal vectors is larger than a certain threshold.

2.5. Rooftop contour extraction

The foregoing procedure collects a set of rooftop facets with rough outline, we now come to extract much more accurate rooftop contour . A manifold approaches are used to extract the contour relying on the spatial structure of the rooftop; concave hull, L_0 regularization and bounding rectangle. The two former are adopted for estimating the contour of a flat or shed rooftop, where the facet is a horizontal plane or an inclined one. Note that the Z axis needs to be rotated in line with the normal vector of the plane firstly. Bounding rectangle is implemented when a gabled or complicated structured rooftop is encountered.

2.5.1. Concave hull

In this step, we apply concave hull to extract the contour of all inliers estimated by RANSAC. A set of inliner indices are projected into individual plane. Herein, the issue domain is transformed from 3D to 2D. Create the voronoi neighborhood for each point on the plane, then define voronoi cells for the concave hull segments. The concave hull vertices then form the final rooftop surface. The voroni neighborhood doesn't specify the number of points to be selected and completely relies on the geometry of datasets. Hence, we can extract rooftop in arbitrary-shape.

2.5.2 L_0 regularization

In practice, a low point density will result in large errors and uncertainties to calculate the rooftop surface. To resolve it, we propose an optimization method relating in spirit to L_0 gradient minimization [12] for further processing.

The common rooftop shapes are polygons consisting of rectilinear with right angles in most urban areas. Take this into account, we use regularized polygon to refine the rooftop contour. In the first place, we ortho-project the points within a rooftop facet onto a 2D plane. Then we need to determine the principal orientation of the projected rooftop, which is the L_0 norm relate to our problem. Attach the origin to the projected centroid to get a straight line l. Rotate the coordinate system to ensure the x-axis is in line with l. Next translate x-axis to the parallel line which pass through the lowest point (x_i, y_{min}). Divide the horizontal axis into unique spaces. Search the max ordinate y_{max} in each space to form a rectangle with x-axis. Then rotate the point set to find out the minimum of all rectangular area with a unique angle in the range $[0, 2\pi)$. Note that the x-axis always pass through (x_i, y_{min}). The result x-axis is the L_0 norm we're looking for. If the divergence of y_{max} between two adjacent rectangles Rec_1 and Rec_2 is small enough, Rec_1 and Rec_2 are merged. Otherwise, we regularize the contour.

2.5.3. Bounding rectangle

The intersection line between inclined planes is defined as a parametrized line:

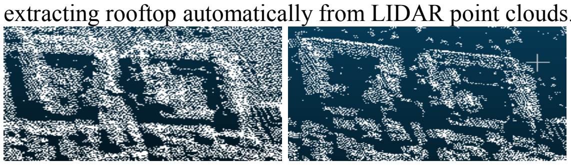
$$l_t = \boldsymbol{o} + t\boldsymbol{p},\ t \in R,$$

where $\boldsymbol{o}$ is the origin, and $\boldsymbol{p}$ is a union normal vector. Then we seek the minimum and maximum of t specifying two points pt_1 and pt_2 on l_t. Define four straight lines (l_1, l_2, l_3, l_4) which not only pass through pt_1 and pt_2 but also is perpendicular to l_t. Next, compute the distances from the points that lie on (l_1, l_2, l_3, l_4) to l_t. The farthest four points are taken as the four vertices of the bounding rectangle. Finally, we refine the contour with the two former approaches.

3. RESULTS AND DISCUSSION

The raw LIDAR datasets selected in this research were collected from the City of Longyan, China. The number of points ranges from 104,432 to 393,651, and the point density is roughly 1.3 pts/m^2. The whole process was implemented in C++. All experiments were performed on Windows 7 operating system. Moreover, the developed segmentation was operated with a fit collection of predetermined thresholds. Take Euclidean based clustering for example, the minimum distance threshold is 2 meters between two clusters in Euclidean space, and the minimum cluster size is 20 points. Fig. 2 shows a raw LIDAR dataset along with the result after ground removal. The effect of object points clustering based on the Euclidean distance is shown in Fig. 3. Then the rooftop facets were obtained by utilizing RANSAC. As illustrated in Fig. 4, extraction of rooftop contour with L_0 regularization achieves much higher precision in comparison with concave hull extraction. Furthermore, the extracted rooftops and the object points were merged together for visual observation as shown in Fig.

5(c). The merged results demonstrate that the proposed segmentation method achieves promising performance in extracting rooftop automatically from LIDAR point clouds.



(a) (b)

Fig. 2. Ground filtering. (a) Raw point clouds. (b) After ground removal.

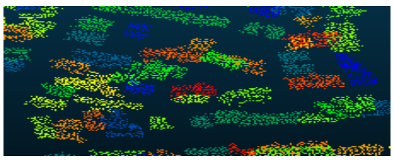


Fig. 3. Object points clustering.

(a) (b)

Fig. 4. Rooftop contour extraction. (a) Before L_0 regularization. (b) After L_0 regularization.

(a) (b) (c)

Fig. 5. Final results. (a) Object points. (b) The extracted rooftops. (c) Merged results.

4. CONCLUSION

In this paper, we have presented a highly effective segmentation method for extracting building rooftop automatically from LIDAR point cloud. The ground points were filtered out from the raw point clouds effectively with a voxel-based upward growing algorithm. The developed Euclidean distance-based method was applied to cluster the non-ground points. Then the RANSAC algorithm was used for estimating building rooftop facets efficiently. In addition, basing on the rooftop structure, the rooftop contours were accurately extracted with concave hull and L_0 regularization. The segmentation results demonstrated the efficiency of our proposed algorithm for building rooftop extraction.

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