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Generating 2D Building Floors from 3D Point Clouds

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Abstract. Laser scanning (LS) is an effective technology for accurately capturing point clouds of visible surfaces of objects in 3D scenes. The point clouds were subsequently used for various applications, for example, generating 2D drawings of the floor or building information models (BIM) and structural inspection. However, in practice, the products from point cloud are created mainly by using commercial software, in which the quality primarily depends on users' experiences and may contain the error caused by technician carelessness. This paper proposed a new method to automatically extract the point clouds of the floor and create a 2D drawing of floor slabs. This method analyses features of the points within cells of a 2D cell grid in the xy plane to extract candidate points of the building and each floor, while the cell- and point-based region growing segmentations were employed to extract the final points of the floor and each edge of the floor, respectively. The proposed method was successfully tested on 7.5 million points of a concrete, two-story building with 17 m long x 7m width x 7m height.

Keywords: Point cloud · Floor extraction · As-built BIM · 2D drawings

1 Introduction

Laser scanning technologies are widely applied in many fields, including civil engineering, architectural design, robotics, and autonomous vehicles [1, 2] because this technology can accurately and quickly capture detailed topographic information of objects' surfaces. Point clouds with x-, y-, and z- coordinates associated with their attributes (e.g., intensity) were used to recognize, detect, and reconstruct 3D models, and so on [3, 4]. Such information can be subsequently integrated into the BIM model, structure inspection, and assessment in civil engineering.

Although creating 3D models of buildings take much attention, generating an accurate 2D floor map still plays an essential role in several applications, such as indoor positioning, robotic autonomous navigation, evacuation, and urban planning. Several methods have been applied to collect the dense point cloud at the building level. For

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example, a terrestrial or mobile laser scanner and/or 2D images based on photogrammetric techniques [5, 6]. Subsequently, many studies have investigated methods for automatically extracting useful information from the point cloud for generating 2D floor maps from point cloud data [7, 8]. One common strategy was to extract floor planes from the point cloud data and then project them onto a 2D plane. This way, the structural elements of concrete buildings were successfully extracted, which the completeness, correctness, and quality from the point-based evaluation [9]. Another method is to identify the intersecting line between the geometry plane of the building. In detail, the 3D line segment features were extracted from an unorganized building point cloud by subsampling, filtering, projection, and dividing the input point cloud into vertical and horizontal planes. For each 3D plane, all points belonging to it were projected onto the fitting plane, and the α-shape algorithm was exploited to extract the boundary points of each plane. The 3D line segments were extracted from the boundary points [10]. A combination of edge detection and segmentation techniques was employed in boundary extraction. For this, deep learning-based methods have also been applied to the problem of point cloud classification and extraction recently [11].

In summary, many methods have been developed to generate 2D floor maps from point cloud data. However, the input parameters of these methods mainly depend on point cloud quality and geometric characteristics. As such, these methods are not robust enough when different types of data and floor geometries are processed. As such, this study proposes an automatic method to process the point cloud of the building to create a 2D floor map. The method combinates a 2D cell grid in the xy plane and a histogram in vertical direction to extract points of the building and then floors. Subsequently, for each set of candidate points of the floor, cell- and point-based region growing were used to extract points of the floor edges while RANSAC was integrated to remove outlier points. By using different types of data structures and processes on the candidate points of an object of interest, the proposed method can potentially handle large-scale point cloud data sets efficiently.

Fig. 1. The point cloud of the House "Haussicht". It has 17 m long x7m width x 7m height, having 2 stories. The point cloud contains more than 7.5 million points.

2 Experimental Data

This study used a 3D point cloud of the House "Haussicht" point cloud. The point cloud of the building was captured by NavVis mobile laser scanning system and published for free access at https://www.navvis.com/resources/specifications/s-vlx-point-cloud-modern-architectural-housing. The house has 17 m length × 7 m width × 7 m height and has two stories with more than 7.5 million points (Fig. 1).

3 Methodology

To generate a 2D floor map from the point cloud of a building, the proposed method, as shown in Fig. 2, consists of three main steps: (1) Extract the point cloud of the building by analyzing the features of cells of a 2D cell grids, (2) extract a point clouds of each floor by combining kernel density estimation and cell-based region growing, and (3) create 2D floor map (Fig. 2).

In Step 1, the point cloud data was decomposed into 2D cell grids in the xy plane, in which predefined cell size (c_s) is used to compute the number of cells in the x and y directions. A pair of opposite corners defined the geometry of each cell in a 3D form: a bottom left—[x_1, y_1, z_{min}] and a top right—[x_2, y_2, z_{max}], in which [x_1, y_1] and [x_2, y_2] are coordinates of grids along the x, and y directions while z_{min} and z_{max} are respectively the minimum and maximum z coordinates of the point cloud within the cell. A cell was classified as full cell if the number of points within the cell was no smaller than the predefined minimum number of points (c_{min_ptc}); otherwise, the cell was known as empty. Notably, only full cells were used in further processing steps.

Next, as the point cloud of the building can be captured from exterior or interior buildings, the point cloud can include non-building objects. The height of cells, which was calculated as the difference between the minimum and maximum z coordinates ($pi.z_{max}$, $pi.z_{min}$) of the points (p_i) within the cell (c_i), was used to group the cells occupy the building points (Eq. 1).

$$c_i = \begin{cases} candidate\ cell,\ if\ c_{hi} \geq c_{h0} \\ other,\ c_{hi} < c_{h0} \end{cases} \quad (1)$$

Where c_{hi} is the height of the cell while c_{h0} is the threshold of the cell height.

Next, the candidate cells are grouped using density-based spatial clustering (DBSCAN) [12], where the minimum sample of 10 and the maximum distance between the samples of 0.5m are used. The points within all available clusters are known as the building points. As such, a sub-cell grid created from the building points was used as input data for Step 2.

In Step 2, a histogram generated from z-coordinates of the building point cloud is used to identify the location of building floors. As the points of the floor are primarily located on the horizontal plane, the histogram's maximum local peak can be the floor's elevation position. As such, in this study, the points within the range of the local peak's margins were recognized as the candidate points of the floor.

$$p_i = \begin{cases} floor\ points, if p.z_1 \leq p.z_i \leq p.z_2 \\ where\ p.z_1 and p.z_2 are\ lower\ and\ upper\ margins\ of\ the\ peak \end{cases} \quad (2)$$

In addition, the cell-based region growing [13] was employed to extract the points of the floor planes based on the candidate points of the floor. In this implementation, the angle of 5 degrees and the distance of 0.01m were set as the thresholds, and the segment having the convex hull area based on its point clouds no smaller than 4m^2 (2.0m wide and 2.0m long) is considered the floor points.

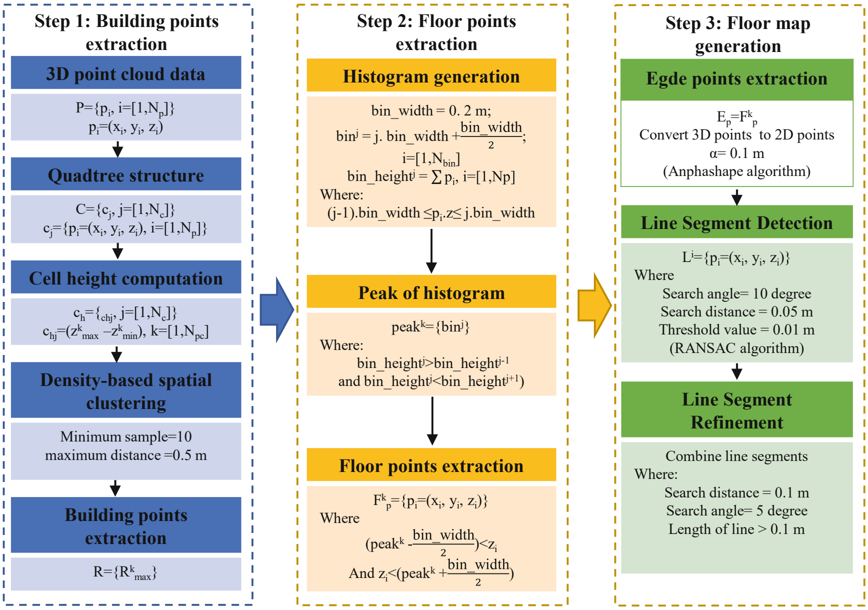

Fig. 2. Flow chart of data processing

In Step 3, edge points of each floor are extracted using the Alpha Shapes algorithm [14], in which the floor point cloud was projected onto its fitting plane, and only x- and y- coordinates of the projected points were used as input data of the alpha shape. The predefined radius of 0.1 m was used as an input parameter to identify the edge points of the floor. Then, the point-based-region-growing was implemented to segment the edge points, in which the angle of 5 degrees and the distance of 0.05m were used as the thresholds, and the residual threshold of 0.005, which is calculated from the neighbor points of the given point on the line, was used as the condition to select the seeding points in a segmentation process. Notably, the radius of 0.2m was used in a range search to get neighbor points in a region growing process. Next, the RANSAC algorithm [15] fixes and identifies the inner points of line segments. Finally, the line segments are refined by checking and grouping the nearest line segments in the same direction again to create the actual edge line of the floor. The size of 0.2 m is m equivalent to the smallest dimension of the building component such as the column. The line segments created by noise points shorter than 0.2m will likely be removed.

4 Results

The characteristics of the point cloud and input parameters for data processing in this study are presented in Table 1. In detail, the cell size is 1.0 m. Region growing starts with a seed cell chosen randomly from the divided cells. The cell height is then calculated for this seed point, and a threshold value is set of 2.0 m to eliminate ground points (Eq. 1). The eight neighboring cells of the seed cell are then checked to see if they meet the criteria for inclusion, based on the cell height threshold. If the adjacent cells satisfy the requirements, they are added to the region, and the process continues with the new point as a seed point. This process is repeated until no more cells can be added to the region. The result is a cluster of points that represent a building region. It is worth noting that the success of the region-growing method heavily depends on the choice of seed points and the criteria for inclusion. The parameters have been carefully considered to ensure accurate building information extraction from the point cloud. With the set of parameters, the building points are successfully extracted from the origin point cloud (Fig. 3a).

Table 1. The characteristics of point cloud and parameters for data processing

Number of points	Mean density (points/m^2)	Average Point Spacing	Parameters					
			Cell size (c_s)	Bin width	Cell height threshold (h_o)	Searching angle	Searching distance	Alpha
7532092	5269	1.3 cm	1 m	0.2 m	2.0 m	5 degree	0.05 m	0.05 m

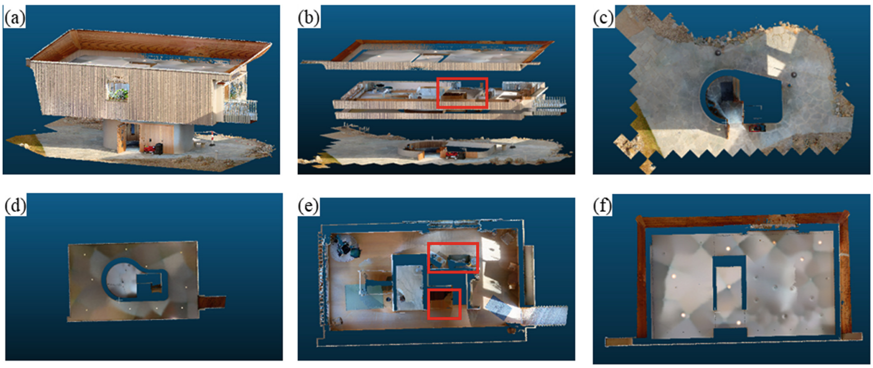

Fig. 3. The visualization of the point cloud. **a** The point cloud of the building after extracted by applying a region-growing algorithm. The location of the ceiling and floor of buildings after extracted in slide view (b) and top view (c-f). The floor point contains many noisy points, which imply the shape of furniture and other facilities inside the house (inside the red rectangles).

In the second step, a histogram of the building points is generated using a bin width of 0.2 m to extract the floor points. The peak of the histogram is identified by checking the bin height value. Subsequently, the points corresponding to the peak and two adjacent bins are extracted. The resulting four sets of point clouds represent two floors and two ceilings, as depicted in Fig. 3. The floor point contains many noisy points, which imply the shape of furniture and other facilities inside the house (Fig. 3b-e).

In the final step, the computational geometry algorithm extracts the edge points. These points correspond to the outermost edges points of the floor. For this, the 3D point cloud of the floor is projected to the 2D, and then the Anphashape algorithm is applied. As a result, the boundary point is extracted from floor points (Fig. 4a-d). Because of the noisy points, the edge points of the furniture are also extracted (Fig. 4d). The original data cause this and can not be automatically removed without considering by humans. However, these misrecognized edge points are expected to be removed when generating line segments. In detail, after getting the 2D edge point cloud of the floor, line segments are identified by considering the group of points which may belong to lines. Because of the different geometry of the curve and straight edge, this step only mentions the method for generating line segments for the straight edge. A line segment can be defined as a geometric construct consisting of a straight line joining two adjacent edge points in the point cloud. The extraction of a line segment from a 2D edge point cloud necessitates the identification of two adjacent edge points that serve as the segment's endpoints. This identification process relies on examining the geometric properties of the objects and respective positions of edge points within 2D space. It enables the line segment to be represented in 2D space, which can be used for visualization or subsequent analysis. The point-based region-growing is applied to the edge points to get each line segment's points. In this case, the criteria are a distance of 0.05 m and a searching angle of five degrees for finding a group of points for each line segment (**Table 1**). Then, the RANSAC algorithm is applied to remove the outliers points, and the line segment's points are calculated from the identified inliner points. Two endpoints identified from the segment's points determine a line segment. As a result, approximately 400 and 600 line segments corresponding to the second floor and ceiling, respectively, are identified (Fig. 4c, d). Then, line segments are refined by grouping the segment in the same direction to get the actual edge line expressing the floor plans. The edge lines are continued and longer than the previous line segments.

Such line segments created from the noisy points will be short. Therefore, they are removed by setting the threshold for the minimum length of 0.2 m of edge lines. Finally, 70 and 85 line segments are identified for the second story's floor and ceiling (Fig. 4e, f). According to the result, the edges are incomplete because of noisy points. It is necessary to improve the resulting quality in the next study by joining line segments. For example, the restoration of line segments due to data loss based on the geometrical features of the object.

Based on the findings of this study, it can be concluded that the data processing approach utilized herein is well-suited for objects situated on a horizontal plane. Implementing an Alphashape algorithm demonstrates significant efficacy when extracting curved and straight edge points (Fig. 4a–d). In the traditional method of estimating the intersection between planes, the curved edged can not be well extracted. Therefore, using the Alphashape algorithm is a good fix for extracting the edge of 2D objects, as in this study. The line segments process also works well for both straight edges. The refining

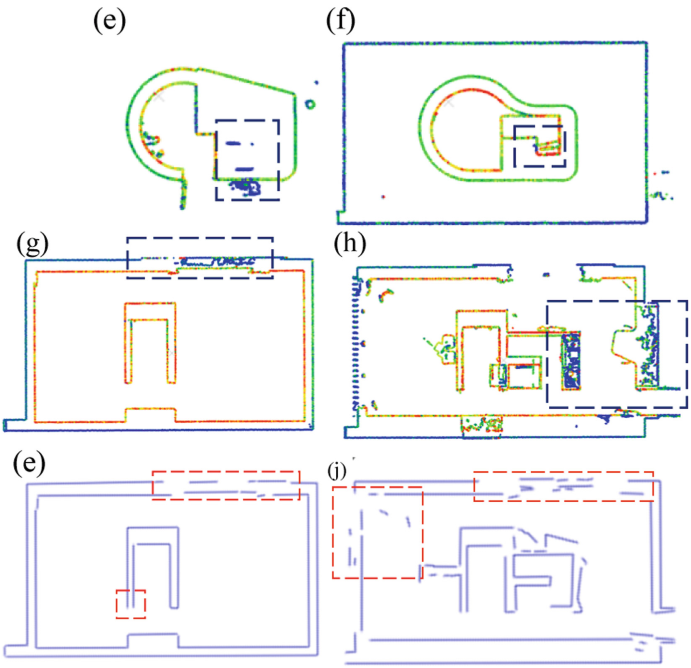

Fig. 4. The result of extracting edge points and generated line segments. Row 1 and 2 imply the extracted edge points of the first and second floors. The line segment'spoints are displayed in different colors for different identified segment lines. Row 3 implies the corresponding 2D floor plans of the floor and ceiling of the second floor. The noisy points are marked inside the blue dashed frames and incomplete line segments are inside the red. Dashed frames.

process of the curve edge is not mentioned in this study because other approach with different parameters should be applied. Good results are achieved for the second floor, where only straight edges appear.

5 Conclusion

This paper presents a method to automatically generate a 2D floor map from mobile laser scanning data, in which the candidate points of the building and then the floors were extracted by using a 2D cell grid in the xy plane and histogram in vertical direction, while the points of floor and floor edges were obtained through cell- and point-based region growing. The proposed method was tested on a dataset of the buildings. As a result, the floor point clouds and the edge points of floors are successfully extracted from the original point cloud. Then, the proposed method creates the straight edge line of the second floor. Because of the noisy points, the edge lines are incomplete. The primary challenge was the size of the data set, which contained billions of points and was computationally intensive to process. Another challenge was the segmentation and classification of the point cloud data, which mainly depended on the set threshold and criteria. This process's accuracy depended on the histogram's cell size and bin width.

Moreover, removing the noisy point caused the missing data, resulting in incomplete edge lines. Therefore, it is necessary to improve the resulting quality in the subsequent study by joining line segments to achieve complete edge lines. Moreover, the developing method for reconstructing the curve edge line is also an exciting topic for the next study.

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