3D Shape Descriptor for Segmenting Point Cloud Data

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Abstract

Object recognition belongs to high-level processing that is one of the difficult and challenging tasks in computer vision. Digital photogrammetry based on the computer vision paradigm has begun to emerge in the middle of 1980s. However, the ultimate goal of digital photogrammetry - intelligent and autonomous processing of surface reconstruction - is not achieved yet. Object recognition requires a robust shape description about objects. However, most of the shape descriptors aim to apply 2D space for image data. Therefore, such descriptors have to be extended to deal with 3D data such as LiDAR(Light Detection and Ranging) data obtained from ALS(Airborne Laser Scanner) system. This paper introduces extension of chain code to 3D object space with hierarchical approach for segmenting point cloud data. The experiment demonstrates effectiveness and robustness of the proposed method for shape description and point cloud data segmentation. Geometric characteristics of various roof types are well described that will be eventually base for the object modeling. Segmentation accuracy of the simulated data was evaluated by measuring coordinates of the corners on the segmented patch boundaries. The overall RMSE(Root Mean Square Error) is equivalent to the average distance between points, *i.e.*, GSD(Ground Sampling Distance).

Keywords : Shape descriptor, Computer vision, Segmentation, Point cloud data

1. Introduction

LiDAR data is one of the major sources to establish spatial information infrastructure since ALS technology has been matured in the early 2000s. ALS technology reaches a degree of the required accuracy in mapping professions and more advanced ALS systems will emerge in accordance with demands in various applications. LiDAR data processing in the field of geomatics includes noise removing, classification and filtering for extracting specific objects (*i.e.*, ground, vegetation, man-made features, *etc.*), clustering for segmentation and grouping for object modeling. Such tasks require sophisticated algorithms especially for automatic approach. Many methods have been developed for building modeling. However, no standard method is available yet.

Most of the aerial surveying companies operate ALS systems for large-scale mapping due to reliability and efficiency of the system. However, to process point cloud data with 3D coordinates obtained by ALS is difficult task especially for implementing automatic method. In general, processing airborne LiDAR data for building modeling consists of following tasks (Vosselman and Dijkman, 2001; Zhang *et al.*, 2003; Lee and Yom, 2005; Kim *et al.*, 2009):

- Noise/outlier removal (if necessary)
- Ground/non-ground separation (or filtering)
- Building extraction
- Roof segmentation (or clustering)
- Data grouping
- Building modeling (mathematical representation)
- Accuracy assessment

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One of the most important parts of LiDAR data processing in building modeling is roof shape description and recognition for surface patch segmentation. Several shape description methods are available such as chain code, Fourier descriptor, signature function, ψ -s curve, octree representation, vertex labeling and so on (Ballad and Brown, 1982; Yi and Schenk, 1992; Gonzalez *et al.*, 2003; Pitas, 2000; Tseng and Wang, 2005; Watt and Policarpo, 1999). However, most of the descriptors aim to recognize 2D objects on the images taken from optical sensors. Segmentation of buildings using LiDAR data involves in identifying and grouping individual surface patch of the roofs. Even though many studies were carried out for more than two decades, segmentation method is not standardized yet and still central issue of the LiDAR data processing.

The purpose of this paper is to utilize chain code in 3D object space for automatic shape description and surface patch segmentation of various roof types. The original chain code was developed to describe 2D objects with direction and length along boundaries of the objects (Freeman, 1961). The chain code representation is simple and straight forward method. However, eight directions used in the chain code are not enough to depict objects correctly. Therefore, shapes of the objects are usually approximated or distorted because of limited number of directional information. In consequence, a certain level of generalization is not avoidable. In addition, chain code representation is not invariant with respect to rotation and scale. Only a few studies related to 3D chain code are found. Bribiesca(2004 and 2007) has proposed a method to represent 3D curves and contour lines derived from DEM(Digital Elevation Model) using 3D chain code for reconstructing topography.

This paper proposes rotation invariant shape recognition strategy and segmentation using multi-cube chain code. The main features of the proposed methodology are that not only surface segmentation but also ground/non-ground data separation and building boundary extraction are performed by the 3D chain code. The results present promising step forward to automatic object reconstruction with airborne LiDAR data. However, some future works are to be considered for improving proposed method as described in the concluding remarks.

2. Multi-cube Shape Descriptor

This section introduces 3D chain code for object detection and shape recognition with point cloud data. The final goal is to carry out surface patch segmentation of the complex-shaped buildings with various polyhedron roofs. The 3D chain code proposed in this paper has a hierarchical cubic structure with sub-cubes. Figure 1-(a) shows chain codes representing 3D directions. Shape of an object could be described by combination of the twenty six directions shown in Figure 1-(b). However, these directions might not be enough to describe detail shape of the objects. Therefore, sub-cubes in the original cube voxels are created to depict more detail shape of the objects. *i.e.*, to increase LoD(Level-of-Detail) of the objects (Figure 1-(c)).

(a) Chain codes (b) 3D directions (c) Multi-cube

Figure 1. 3D chain code cube.

The advantage of using chain code compared with utilizing only slope angle information between points is that the chain code provides slope, directional information and length with systematic fashion. Therefore, shape of an object can be described by rule based compact representation that eventually makes possible to reconstruct the object by decoding process. *i.e.*, classification of the codes leads not only segmentation of the point cloud data but also reconstruction of the objects.

However, implementing chain code to the LiDAR data requires gridding to make regularly tessellated data because of the nature of chain code operator. Figure 2 demonstrates significance of the sub-cube for object recognition. Determination of level of the sub-cube depends on resolution of the data (*i.e.*, GSD) and required LoD of the objects. If processing starts with small cube (*i.e.*, size is one-third of the original cube at the first level), it is sensitive to the noise and might provide incorrect results. In this case,

segmentation is quite difficult because each surface patch does not have dominant chain code, *i.e.*, noisy result with mixed chain codes in the patch.

(White circles represent current point, *i.e.*, center of cube, and arrows depict cube moving direction.)

Figure 2. Comparison between results from original-cube and multi-cube.

3. Segmentation Scheme

Man-made structures such as buildings consist of patches of planes and/or curved surfaces that could be represented by mathematical functions. Therefore, it is significant to identify and separate patches for segmentation. Human beings easily recognize patches of different shapes based on the size, rotation, slope, curvature, *etc.*. The important issue is that shape descriptors and object recognition method should be invariant with geometric transformations such as translation, scale, and rotation. Therefore, as shown in Figure 3, the cube is applied to four directions; parallel to X - and Y -axis, and two diagonal, namely X , Y , $N-E$, and $S-E$ directions.

Figure 3. Four directions of applying cube.

Finally results from all directions are to be integrated. A building shown in Figure 3 is gambrel roof that has symmetrical two-sided roof with two slopes on each side and the lower slope is steeper than upper one. Human beings can easily describe the characteristics of the object shape under the geometric transformations.

Figure 4. Procedure of patch segmentation.

Figure 4 demonstrates segmentation strategy of the multi-cube chain code for a gambrel roof shown in Figure 3. It is important to note that applying only one direction could not recognize shape of the roof correctly. In addition, two different slopes of the roof surfaces could be differentiated by utilizing sub-cube. That is the reason why we suggest that the descriptor was applied in four directions with sub-cube.

To determine whether the sub-cube is necessary or not, first slope using heights of current point and next point was computed with the original cube that yields chain codes; 9, 10, 1, 19 or 18 (Figure 1-(a)). Then, slope with the same points with sub-cube having one-third size of the original cube was computed. If the codes using original and sub-cube are the same the sub-cube is not necessary, otherwise the sub-cube is necessary. Therefore, basically flat planes or surfaces with lower slope angle do not need sub-cube, otherwise, multi-cube chain code is mandatory.

Finally the results from each direction were combined to segment surface patches. Detail explanation of the procedure is as follows:

- Figure 4-(a) shows chain codes from four directions.
- Figure 4-(b) represents sub-cube (Index 0 and 1 denote that sub-cube is not used and sub-cube is used, respectively).
- Figure 4-(c) shows segmentation results from combining chain code (Figure 4-(a)) and sub-cube index (Figure 4-(b)) for each direction.
- Figure 4-(d) was the final segmentation results by combining segmentation from each direction. (where *A*, *B*, *C*, and *D* denote segmented patch.)

4. Experimental Results

4.1 Point cloud data

Two datasets were used; simulated point cloud data and real airborne LiDAR data. The simulated data is composed of six typical buildings with various polyhedron roofs; *i.e.*, gable, gambrel, mansard, hip, jerkinhead, dome(*i.e.*, hemisphere), intersecting gable, and pyramidal roof (Figure 5 and Figure 6-(a)). Random noises with $\pm 0.1\text{m}$ were added to the simulation data. The real data was collected at the University of Calgary campus (Figure 6-(b)). A part of the real data was used to evaluate performance of the proposed method. The average point distances of the simulated data and real data are 0.25m and 0.6m, respectively. Gridded data is required due to nature of the $3 \times 3 \times 3$ cube descriptor.

Many interpolation methods are available. In this paper, simple nearest neighbor interpolation was applied for gridding irregularly distributed point cloud data. The interpolation is not the main topic of this paper, and the proposed scheme does not depend on the interpolation method. The grid sizes of the simulated and real data are $0.25\text{m} \times 0.25\text{m}$ and $0.6\text{m} \times 0.6\text{m}$, respectively in accordance with the average GSD.

Figure 5. Simulation data of various roofs.

(a) Simulated point cloud data

(b) Airborne LiDAR data (University of Calgary)

Figure 6. Test datasets after gridding

4.2 Surface Patch Segmentation and Analysis

The segmentation results are presented by taking simulated mansard roof data (Figure 7) as an example. The mansard is four-sided roof having a double slope on all sides. It is noted that the upper slope is steeper than the lower one. Procedure of patch segmentation was performed as follows (Figure 8):

- Chain code generation for each direction using multi-cube (*i.e.*, circled numbers denote chain codes)
- Combining sub-cube code results for each direction
- Combining chain code and sub-cube information
- Final segmentation by combining intermediate results from pervious step

Figure 7. Mansard roof data.

Above steps are also explained in Figure 4. Finally, additional processing was required for grouping segmented data as homogeneous patches. The pixels that do not belong to any segmented group were compared with surrounding pixels, then, the pixels were enforced to belong to the surrounding group.

Direction	X	Y	N-E	S-E
(a) Chain code
(b) Sub-cube index
(c) Segmented patches by combining chain code and sub-cube index
(d) Segmented surface patches

(Circled numbers indicate chain codes. In sub-cube index, black areas require sub-cube and white areas does not require sub-cube. Circled alphabet letters indicate segmented group.)

Figure 8. Result of chain codes, sub-cube and segmentation for mansard data.

Shapes of the roofs in the simulation data were properly recognized. In consequence, segmentation was performed correctly. The 3D chain code with sub-cube is necessary to describe and segment objects in detail. Most of the roof tops in the real LiDAR data are flat, therefore, sub-cube was applied to only small parts of the roofs. It is noted that dome (*i.e.*, hemisphere) in the lower right building in Figure 9-(a) was segmented several patches because surface of the dome consists of small patches with different slopes; steepest slope in the lower area and flatter in the upper area. Segmentation result from real LiDAR data looks reasonable based on visual inspection. Boundaries and shapes of the buildings were well identified and represented. Also, super structures of the roofs were segmented (Figure 6-(b) and Figure 9-(b)).

(a) Simulated data

(b) University of Calgary data

Figure 9. Segmentation results.

As for representing or modeling of such curved surfaces, there might be two ways:

- Modeling with planes of segmented patches
- Modeling with a mathematical surface for example, polynomials, or hemisphere by least-squares (*i.e.*, surface fitting) (Figure 10)

In case of fitting with hemisphere, the initial approximations of center coordinates and radius of the hemisphere are required to solve linearized hemispheric function and the procedure is as follows (Yoo *et al.*, 2011):

Figure 10. Surface fitting with hemisphere.

$$f(a, b, c, r) := (X-a)^2 + (Y-b)^2 + (Z-c)^2 - r^2 = 0 \quad (1)$$

where X , Y , and Z are coordinate of points. a , b , c , and r are location of center and radius of the hemisphere, respectively. The linearized form of Equation (1) by Talyor expansion is:

$$f(a_0, b_0, c_0, r_0) := \frac{\partial f}{\partial a} \Big|_{a_0} da + \frac{\partial f}{\partial b} \Big|_{b_0} db + \frac{\partial f}{\partial c} \Big|_{c_0} dc + \frac{\partial f}{\partial r} \Big|_{r_0} dr = 0 \quad (2)$$

where a_0 , b_0 , c_0 , and r_0 are the initial approximations. da , db , dc , and dr are the increment of the solutions at each iteration. The parameters in Equation (2) are solved by:

$$\xi = (A^T P A)^{-1} A^T P y \quad (3)$$

Variance component of the observations is determined by:

$$\text{var. comp} = \text{SQRT} [SUM(residual^2)/(n-m)] \quad (4)$$

where n and m are number of points and number of unknowns, respectively. The RMSEs of estimated parameters are computed by:

$$RMSE(a, b, c, r) = \text{var. comp} [diag(A^T P A)^{-1}]^{1/2} \quad (5)$$

where ξ denotes unknown vector; $[da, db, dc, dr]^T$. A is design matrix of partial differential coefficients with respect to unknown parameters. P is weight with identity matrix in this case. y represents observation vector $[X, Y, Z]^T$ from LiDAR data.

The dome in Figure 5-(b) was modeled with hemispheric function and the final results are shown in Table 1. Variance component of the observations is 0.254m that is equivalent

Table 1. Modeling of dome and accuracy (Unit: m).

Parameter	True value	Estimation	Variance component	RMSE
a	70.00	70.000	0.254	0.005
b	65.00	65.007		0.005
c	15.00	15.001		0.010
r	5.00	5.003		0.070

to the GSD (*i.e.*, 0.25m). RMSE of each parameter indicates that the estimations are reliable.

4.3 Accuracy of Segmentation

In order to evaluate accuracy of the segmentation, the coordinates of the segmented patch corners were measured. RMSEs could be computed since true coordinates of the corners of the simulated data are known. RMSEs of X and Y coordinates, and planimetric RMSE were computed by:

$$RMSE_x = \text{SQRT} [SUM(residual_x^2)/n] \quad (6)$$

$$RMSE_y = \text{SQRT} [SUM(residual_y^2)/n] \quad (7)$$

$$RMSE_{plane} = \text{SQRT} [RMSE_x^2 + RMSE_y^2] \quad (8)$$

where *residual* is difference between true values and measurements, and n denotes number of corner points of the segmented patches (Total 127 point). Tables from 2-(a) to 2-(e) show X and Y coordinates differences between true coordinates and measured, and RMSE of the simulation data. The overall RMSEs are listed in Table 3.

RMSE of X and Y coordinates are around size of GSD (0.25m $\times$ 0.25m), and the overall planimetric RMSE is 0.33m that is quite acceptable by considering GSD. However, accuracy of the University of Calgary data could not be evaluated because the reference data are not available at this time.

Table 2. Accuracy of simulation data (Unit: m).

(a) Pyramid/Gable roof

True coordinates		Measured coordinates		Residual	
X	Y	X	Y	DX	DY
5.00	45.00	5.25	45.25	-0.25	-0.25
5.00	50.00	5.25	50.00	-0.25	0
5.00	55.00	5.50	54.75	-0.50	0.25
20.00	30.00	20.25	30.25	-0.25	-0.25
20.00	45.00	20.25	45.25	-0.25	-0.25
20.00	50.00	20.25	50.00	-0.25	0
20.00	55.00	20.25	55.00	-0.25	0
20.00	70.00	20.25	70.00	-0.25	0
25.00	30.00	25.00	30.25	0	-0.25
25.00	45.00	25.00	45.25	0	-0.25
25.00	50.00	25.00	50.25	0	-0.25

25.00	55.00	25.00	55.25	0	-0.25
25.00	70.00	25.00	70.00	0	0
30.00	30.00	30.00	30.25	0	-0.25
30.00	45.00	30.00	45.25	0	-0.25
30.00	50.00	30.25	50.00	-0.25	0
30.00	55.00	30.25	55.25	-0.25	-0.25
30.00	70.00	30.00	69.75	0	0.25
45.00	45.00	45.25	45.25	-0.25	-0.25
45.00	50.00	45.00	50.00	0	0
45.00	55.00	45.00	54.75	0	0.25
RMSE				0.20	0.20
Planimetric RMSE				0.28	

(b) Dome/Gable roof

True coordinates		Measured coordinates		Residual	
X	Y	X	Y	DX	DY
50.00	60.00	50.25	60.25	-0.25	-0.25
50.00	65.00	50.25	65.00	-0.25	0
50.00	70.00	50.25	70.00	-0.25	0
65.00	60.00	65.25	60.25	-0.25	-0.25
65.00	65.00	65.25	65.00	-0.25	0
65.00	70.00	65.25	70.00	-0.25	0
75.00	60.00	75.25	60.25	-0.25	-0.25
75.00	65.00	75.00	65.00	0	0
75.00	70.00	75.25	70.00	-0.25	0
90.00	60.00	90.25	60.25	-0.25	-0.25
90.00	65.00	90.00	65.00	0	0
90.00	70.00	90.25	70.00	-0.25	0
RMSE				0.23	0.14
Planimetric RMSE				0.27	

(c) Complex gable roof

True coordinates		Measured coordinates		Residual	
X	Y	X	Y	DX	DY
60.00	30.00	60.25	30.25	-0.25	-0.25
60.00	32.50	60.25	32.50	-0.25	0
60.00	35.00	60.25	35.25	-0.25	-0.25
60.00	45.00	60.25	45.25	-0.25	-0.25
60.00	50.00	60.25	50.25	-0.25	-0.25
63.75	35.00	64.00	35.25	-0.25	-0.25
63.75	40.00	64.00	40.00	-0.25	0
63.75	45.00	64.00	45.25	-0.25	-0.25
67.50	30.00	67.75	30.25	-0.25	-0.25
67.50	32.50	67.75	32.50	-0.25	0
67.50	35.00	67.75	35.25	-0.25	-0.25
67.50	45.00	67.75	45.25	-0.25	-0.25
67.50	50.00	67.75	50.25	-0.25	-0.25
75.00	30.00	75.25	30.25	-0.25	-0.25
75.00	35.00	75.25	35.25	-0.25	-0.25
75.00	45.00	75.25	45.25	-0.25	-0.25
75.00	50.00	75.25	49.75	-0.25	0.25
76.87	47.50	77.00	47.75	-0.12	-0.25
78.75	30.00	78.75	30.25	0	-0.25

78.75	35.00	79.00	35.25	-0.25	-0.25
78.75	40.00	79.00	40.00	-0.25	0
78.75	45.00	79.00	45.25	-0.25	-0.25
80.62	47.50	80.50	47.50	0.12	0
82.50	30.00	82.75	30.25	-0.25	-0.25
82.50	35.00	82.75	35.25	-0.25	-0.25
82.50	45.00	82.75	45.25	-0.25	-0.25
82.50	50.00	82.75	49.75	-0.25	0.25
RMSE				0.24	0.23
Planimetric RMSE				0.33	

(d) Intersecting hip roof

True coordinates		Measured coordinates		Residual	
X	Y	X	Y	DX	DY
20.00	10.00	20.25	10.25	-0.25	-0.25
20.00	20.00	20.50	20.00	-0.50	0
21.25	13.75	21.50	14.25	-0.25	-0.50
21.25	16.25	21.50	16.25	-0.25	0
22.50	10.00	23.50	10.25	-1.00	-0.25
22.50	20.00	23.25	20.25	-0.75	-0.25
23.75	13.75	23.75	14.25	0	-0.50
23.75	16.25	23.75	16.25	0	0
25.00	12.50	25.00	12.25	0	0.25
25.00	17.50	25.00	18.00	0	-0.50
27.50	10.00	27.25	10.25	0.25	-0.25
27.50	15.00	28.00	15.00	-0.50	0
27.50	20.00	27.00	20.25	0.50	-0.25
30.00	12.50	30.25	12.75	-0.25	-0.25
30.00	17.50	30.25	18.00	-0.25	-0.50
32.50	15.00	32.75	15.00	-0.25	0
35.00	12.50	35.00	13.00	0	-0.50
35.00	17.50	35.00	17.50	0	0
RMSE				0.39	0.31
Planimetric RMSE				0.50	

(e) Gambrel roof

True coordinates		Measured coordinates		Residual	
X	Y	X	Y	DX	DY
50.00	10.00	50.25	10.25	-0.25	-0.25
50.00	12.50	50.25	12.5	-0.25	0
50.00	15.00	50.25	15.00	-0.25	0
50.00	17.50	50.25	17.50	-0.25	0
50.00	20.00	50.25	20.25	-0.25	-0.25
51.87	10.00	52.00	10.25	-0.13	-0.25
51.87	11.25	52.00	11.25	-0.13	0
51.87	18.75	52.00	18.75	-0.13	0
51.87	20.00	52.00	20.25	-0.13	-0.25
52.50	13.75	52.75	14.00	-0.25	-0.25
52.50	15.00	52.75	15.00	-0.25	0
52.50	16.25	52.50	16.50	0	-0.25
55.00	13.75	55.00	14.00	0	-0.25
55.00	15.00	55.00	15.00	0	0
55.00	16.25	55	16.50	0	-0.25

55.62	10.00	55.75	10.25	-0.13	-0.25
55.62	11.25	55.75	11.25	-0.13	0
55.62	18.75	55.25	18.75	0.37	0
55.62	20.00	55.25	20.25	0.37	-0.25
59.37	10.00	59.75	10.25	-0.38	-0.25
59.37	11.25	59.75	11.25	-0.38	0
59.37	18.75	59.25	18.75	0.12	0
59.37	20.00	59.25	20.25	0.12	-0.25
60.00	13.75	60.00	14.00	0	-0.25
60.00	15.00	60.00	15.00	0	0
60.00	16.25	60.00	16.25	0	0
62.50	13.75	62.75	14.00	-0.25	-0.25
62.50	15.00	62.75	15.00	-0.25	0
62.50	16.25	62.75	16.25	-0.25	0
63.12	10.00	63.25	10.25	-0.13	-0.25
63.12	11.25	63.25	11.25	-0.13	0
63.12	18.75	63.25	18.75	-0.13	0
63.12	20.00	63.25	20.25	-0.13	-0.25
65.00	10.00	65.25	10.25	-0.25	-0.25
65.00	12.50	65.25	12.5	-0.25	0
65.00	15.00	65.25	15.00	-0.25	0
65.00	17.50	65.00	17.50	0	0
RMSE				0.21	0.17
Planimetric RMSE				0.27	

(f) Mansard roof

True coordinates		Measured coordinates		Residual	
X	Y	X	Y	DX	DY
110.00	10.00	110.25	10.50	-0.25	-0.50
110.00	20.00	110.25	20.00	-0.25	0
112.50	12.50	113.00	12.75	-0.50	-0.25
112.50	17.50	112.75	17.25	-0.25	0.25
113.75	13.75	113.75	13.75	0	0
113.75	16.25	113.75	16.25	0	0
116.25	13.75	116.50	13.75	-0.25	0
116.25	16.25	116.50	16.25	-0.25	0
117.50	12.50	117.50	12.50	0	0
117.50	17.50	117.50	17.25	0	0.25
120.00	10.00	120.00	10.75	0	-0.75
120.00	20.00	120.00	20.25	0	-0.25
RMSE				0.22	0.30
Planimetric RMSE				0.37	

Table 3. Overall RMSE of simulation data (Unit: m).

RMSE _x	RMSE _y	RMSE _{plane}
0.25	0.22	0.33

It is noted that most of the residuals have negative values (from Tables 2-(a) to 2-(f)). Figure 11 explains such bias or dislocalization that might be caused by interpolation of the point cloud data and definition of the object or patch boundaries. The boundaries (or edges) and corner points

were computed by detecting location of abrupt change (*i.e.*, from small to large value or *vice versa*).

(Black pixels represent true patch boundary and gray pixels represent segmented patch.)

Figure 11. Dislocalization of segmented patch.

5. Concluding Remarks

The most difficult and important part in airborne LiDAR data processing is to segment surface patches of the roof structure. Shape recognition and analysis are crucial in segmentation and modeling. LiDAR data provides irregularly distributed coordinates of the surfaces with lack of the semantic and visual information. Therefore, data processing is quite challenging especially to achieve automatic procedure.

This paper applied chain code method in 3D object space for automatic segmentation of point clouds and characterization of the segmented surface geometry. The proposed method was performed to the simulation and real data. Simulation data includes more complicated polyhedron roof shapes than real world data. In order to be rotation invariant shape descriptor, the cube with 3D chain code was applied four directions. Sub-cube is necessary to recognize detail shapes correctly. The main features of the proposed method can be summarized as follows:

- Shape descriptors for image processing could be expanded to 3D object recognition method.
- Rotation invariant property is one of the most important issues for segmenting meaningful objects from the point cloud data.
- The overall accuracy of the segmentation was equivalent to GSD of the data.

- There might be limitation to segment curved surfaces with 3D chain code.

As for the future works, some important tasks that make 3D chain code more robust method include:

- Automatic detection of the representative features of objects (*i.e.*, 3D model key points, adjacency of surface patch, topology among segmented patches, *etc.*)
- Modeling surfaces with appropriate mathematical representation
- Processing irregularly distributed point cloud data without gridding
- Separation of target objects (*i.e.*, buildings) and unnecessary objects (*i.e.*, trees, vegetation and/or other features especially close to the target objects)

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