Dome Extraction from Airborne LiDAR Point Cloud

Abstract

This work aims to adapt traditional Hough Transformation (HT) to extract dome structure from airborne LiDAR Point Cloud. Traditional HT is widely used in line and circle detection due to its robustness to noises and missing data. But suffering from the high storage and computation requirement resulting from its parameter voting mechanism, it usually works for models with less than three unknown parameters in application. In this paper, we propose to decompose the 3D point clouds into 2D segments along the scanline. HT is then used to detect arcs in the 2D space and the parameter space is further decreased to one dimension by coordinates transformation. Experiments over two typical experimental areas demonstrate the effectiveness of this method.

1. Introduction

Urban reconstruction is a classical field in photogrammetry and remote sensing community and also attracts interests and gives rise to a lot of research work in computer graphics and computer vision communities. It benefits a wide range of applications, from entertainment industry, digital mapping for mobile devices, to urban planning, emergency management and disaster control. As the main infrastructure of the urban area, creation of the 3d geometric model of individual buildings, facades and even further details is one of the major tasks in urban reconstruction.[1] The light ranging and detection (LiDAR) technique provides an efficient way to tackle this task by acquiring 3D dense point clouds directly. Extracting buildings from these point clouds is an important part in the reconstruction procedure, since buildings can be modeled when they are separated apart. Although it needs to determine each point belongs to which segment before finally getting the vectorized 3D model, there may be no necessity to extract dome structure alone in large-scale scenes for urban reconstruction, since it may be merged into a unified building extraction and roof segmentation processing framework, which can deal with various roof structure, like using clustering technique or represented as a global minimization problem solved by optimization method.

But there are truly some efforts to extract spheres in different scenarios, like indoor and close-range scenes, serving for different application purposes. In [2, 3], 3D HT is directly used to detect spheres with some strategies to constrain the memory and computation cost while keeping the detection accuracy. In [4, 5], variants of RANSAC algorithm are adopted to fit the spherical shape by modifying the small point sets choosing strategy and geometrical fitting techniques. These methods are not heavily limited by the dimension of the parameter space, thus can relieve the storage and computation cost suffered in 3D HT, but still need manual efforts to adjust some parameters, like distance thresholds [6], and generalize poorly in multi-model case, especially with high levels of noise and clutter [7]. In [6], which is inspired from [7, 8], an energy function is formulated after the initial model fitting, and solved by an optimization method, which provides a more robust, accurate, and generalizable solution. In fact, [7, 8] represent a class of elegant algorithms, which are widely used in a bunch of vision tasks, especially in the pre-deep-learning era.

Therefore, this work doesn't try to prove that it defines a meaningful question. And since there aren't comparison experiments between this method and 3D HT, RANSAC-based method, energy-based method, it also won't prove that it proposes a superior solution in algorithm performance (in fact it fails in small arcs which usually lie near the edge of dome structure, and requires some manual adjusting work). The contribution of this work is just to provide a possible solution to extend HT to a higher dimension while reducing the storage and computation costs at the same time in the dome extraction specific task context.

2. Methodology

The procedure of the proposed method mainly includes two stages, scanline segmentation and arcs detection. After filtering out the ground points by existing mature algorithm, the remaining points will be separated into segments along the scanline. Only those segments whose curvature changes smoothly and including enough points will be fed into arcs detection part. These two stages will be illustrated in Section 2.1 and 2.2.

2.1 Scanline Segmentation

Douglas-Peucker algorithm [9] is originally developed for cartographic generalization to get a simplified form of a curve or polygon. As shown in Figure 1, given a curve composed of multiple points, this algorithm will filter out those points whose distance to the line formed by their left and right neighbor is shorter than the distance threshold. In this work's experiment context, the airborne laser scanner scans the terrain surface in a repeated Z manner. Thus, feed the points' projection in the XOY plane to the DP algorithm, the feature points at each peak of the Z scanlines are kept and the whole area are separated as line segments defined by these feature points.

Then start from the highest point of each line segment, march in the two opposite directions along the line to search for the point whose curvature change is within the threshold compared with its neighbors to form the feature arcs. Those feature arcs which contain enough points will serve as candidate arcs to be filtered by HT.

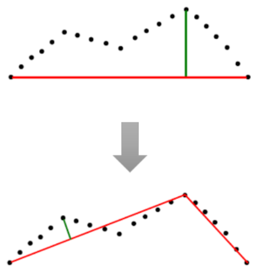


Figure 1. Douglas-Peucker algorithm can keep the most important feature points in curves. It is used to segment point cloud scanlines in this method.

2.2 Arcs detection

The traditional HT [10] to detect circles in images is based on the following equation:

$$(x-a)^2+(y-b)^2=r^2 \tag{1}$$

where (a, b) is the center of a circle and r is the radius. The relation between the original space (x, y) to the parameter space (a, b, r) can be expressed by Figure 2. In this work, set the original point at the highest point of every scanline segment, as shown in Figure 3, and transform the coordinates of the original point clouds according to the following equations:

$$x'_{ij}=\sqrt{(x_{ij}-x_{i0})^2+(y_{ij}-y_{i0})^2} \tag{2.1}$$

$$y'_{ij}=\left|z_{ij}-z_{i0}\right| \tag{2.2}$$

where x'_{ij} represents the transformed coordinate of the jth point on the ith scanline segment, x_{ij} represents the original coordinate of the jth point on the ith scanline segment. Then the circle can be expressed mathematically by:

$$x^2 + y^2 = 2Rx \quad (3)$$

In this way, the parameter space is reduced to one dimension, which exponentially relieved the storage and computation burden. For every point in the candidate arcs, calculate the corresponding R according to the above equation and accumulate the votes in the parameter space discretized by R_inv. Those candidate arcs whose peak vote in the accumulator of parameter space is larger than the threshold will be marked as belonging to a dome structure.

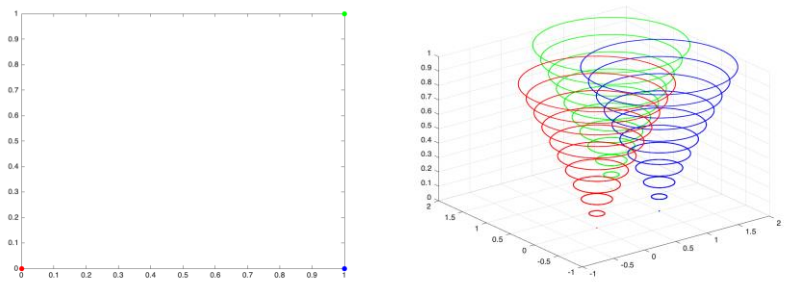


Figure2[11]. The traditional HT maps a point on a circle in 2D space (x, y) to a cone in a three dimensional parameter space (a, b, r).

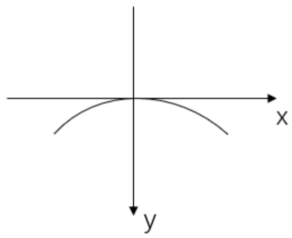
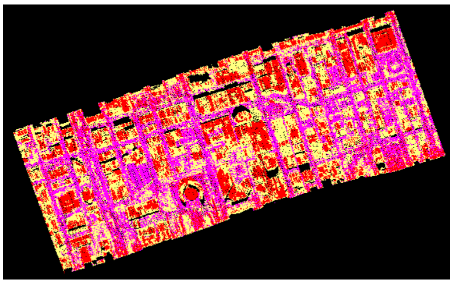


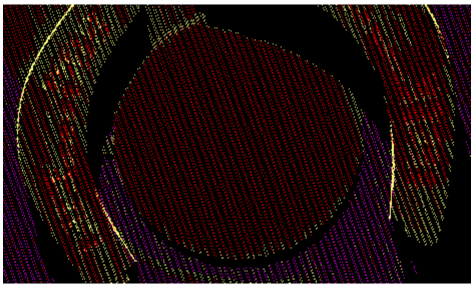
Figure3. The transformed coordinate system to represent a circle

3. Experiments & Results

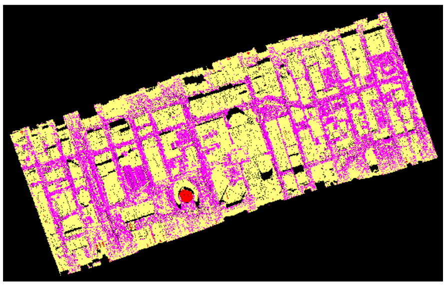
There should be some measure metrics calculated from TP, FP, TN, FN, like completeness $=TP/(TP + FN)$, correctness$=TP/(TP + FP)$, etc. Since these parameters are not listed in the original script, they are omitted here. And the following will just give some qualitative analysis.

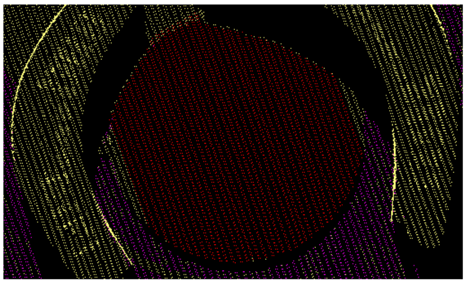
This method is mainly tested on a regular and a noisy area. The detailed description of these areas is also not listed in the original version, so this part will also be omitted. The experiment results are shown in Figure3 and Figure4. They reflect some common characteristics of this method. First, it truly computes fast. Running at Lenovo y470 (Intel Core i5 2330M), the computation will finish in 10 seconds even with 1,300,000 points in the area. And by adjusting the parameters carefully, it will effectively extract the target dome out in different cases. But there are also truly some disadvantages of this method. First, it fails at the edge of the dome structure where the arcs contain not enough points to be selected out as candidate arcs or be detected as targeted arcs. In order to detect these arcs out, the threshold should be set lower and this will also give rise to some false detection in other similar structure. Second, in order to reduce the computation complexity, this method sacrifices the robustness. It is sensitive to the sudden change in curvature caused by noises, and the manual adjusting work, like setting various thresholds and the range of R will heavily influence the final detection result.





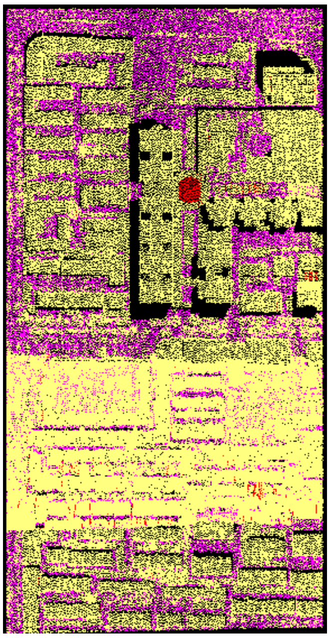
The selected candidate arcs in the whole area   The candidate arcs in the targeted area

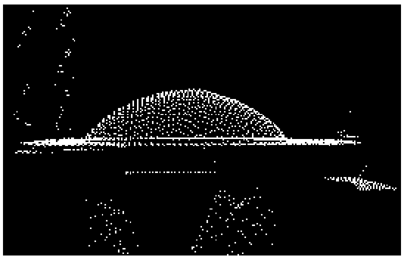




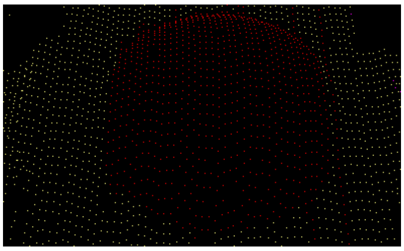
The detected dome viewed in the whole area   The detected dome viewed in the targeted area

Figure4. The experiment results in the regular case





Original data in the targeted area



Detected dome in the targeted area

Candidate arcs   Detected dome

Figure5. The experiment results in the noisy case

4. Conclusion & Discussion

Considering the dimension curse in HT, this work decomposes the original point clouds into line segments along the scanline and further decreases the parameter space to one dimension by coordinate transformation based on the geometric prior. Experiments on the regular and noisy areas demonstrate the effectiveness of this method, although it may sacrifice the robustness and introduce some manual labor.

Not restricted in the urban reconstruction scenario, and viewed from other academic discipline, like computer vision (or robotics vision), this task can be formulated as some meaningful problem like 3D instance segmentation, which may bring in some insights and creativity.

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Road Segmentation in Rural and Urban Areas

1. Experiments

1.1 Apply GrabCut to global area

For the experimental area that sharp gradient variation exists at the edges of road area and the road network structure is simple, Mean-shift segmentation is applied and the shape index is used to filter out the road area prior. A post-processing step, based on GrabCut, built upon over-segments, is used to optimize the segmentation result.

1.1.1 In the case of simple rural area

Original Image

Histogram Equalization

Original Meanshift Segmentation

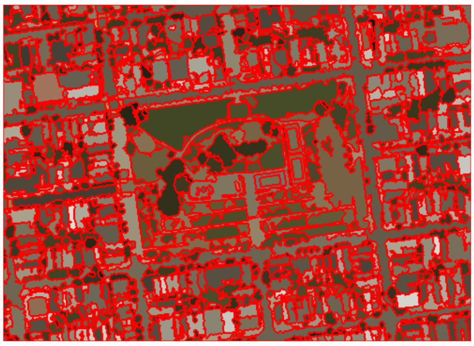
Merging Small Patches into Larger Ones

Shape Index Filtering Overlapping the Road Area Prior on the Original Image

GrabCut Post-processing on the Over-segmented Image

1.1.2 In the case of complex urban scene

Case1



Original Image Meanshift Segmentation

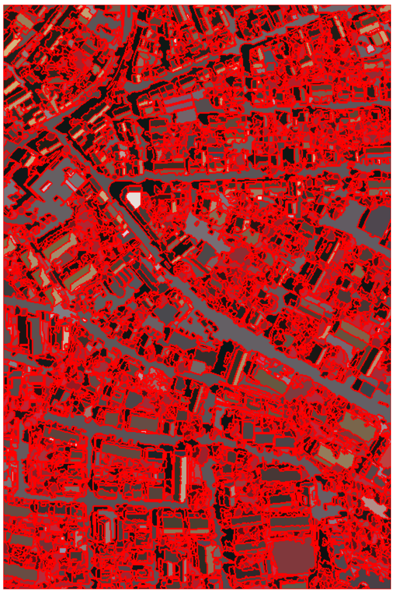
Road Prior after Shape Index Filtering

SLICO Super-pixel Segmentation

GrabCut Post-processing on the Over-segmented Image

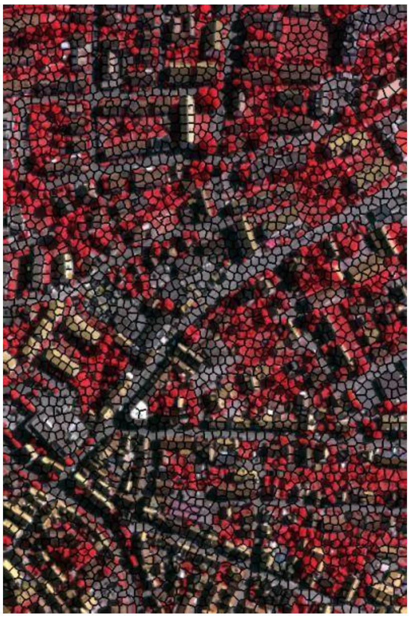
Case2

Original Image



Meanshift Segmentation

Shape Index Filtering



SLICO Super-pixel Segmentation

GrabCut Post-processing on the Over-segmented Image

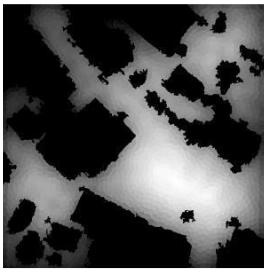
1.2 Apply GrabCut to each local patch along the road

For the experimental area that is complex in the scene, the disparity map is used to get the terrain mask of the original image. After conducting the foreground and background prior selection process based on connected component analysis and NDVI index, the GrabCut post-processing step built upon pixels is used in every window got along the road.

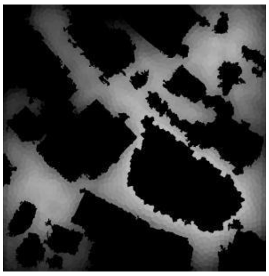
Original Image

Filter Out the Objects above the Ground by Disparity Map from SGM

Connected Component Analysis to Filter Out Noises and Fill the Holes



The Area Saliency Computation based on ATS

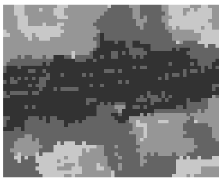


Filter Out the Area Connected with Roads Using Area Saliency Map

The Original Binary Map

The Original Image Patch

The Foreground Prior



The Prior Mask

The GrabCut Segmentation Result

Original Image Patch

The Direction of the Road

Segmentation Result after Patch-wise GrabCut