Delineation of Individual Tree Crowns for Mobile Laser Scanning Data

Rosen Wu[a], Yiping Chen*[a], Chenglu Wen[a], Cheng Wang[a] and Jonathan Li[a, b]
[a]Fujian Key Laboratory of Sensing and Computing for Smart Cities,
Xiamen University, Xiamen, China;
[b]GeoSTARS Lab, Department of Geography and Environmental Management,
University of Waterloo, Waterloo, Ontario N2L 3G1, Canada
ypchenhk@gmail.com

ABSTRACT

The information of individual trees plays an important role in urban surveying and mapping. With the development of Light Detection and Ranging (LiDAR) technology, 3-Dimenisonal (3D) structure of trees can be generated in point clouds with high spatial resolution and accuracy. Individual tree segmentations are used to derive tree structural attributes such as tree height, crown diameter, stem position etc. In this study, a framework is proposed to take advantage of the detailed structures of tree crowns which are represented in the mobile laser scanning (MLS) data. This framework consists of five steps: (1) Automatically detect and remove ground points using RANSAC; (2) Compress all the above ground points to image grid with 3D knowledge reserved; (3) Simplify and remove unqualified grids; (4) Find tree peaks using a heuristic searching method; (5) Delineate the individual tree crowns by applying a modified watershed method. In an experiment on the point clouds on Xiamen Island, China, individual tree crowns from MLS point cloud data are successfully extracted.

Keywords: individual tree delineation, mobile light detection and ranging (LiDAR), point clouds, improved watershed segmentation

1. INTRODUCTION

With the fast development of economy and urbanization, the ecological environment around our human settlements has been deteriorating. Therefore, more attention has been paid to the ecosystem in human settlements. Trees play a significant role in this system and our human beings are connected to the nature through trees. Individual tree segmentations have important implications in forestry [1-3]. Once accurately segmented, tree structural attributes such as tree height, crown diameter, canopy based height, basal area, diameter at breast height (DBH), wood volume, and species type can be further derived [4, 5].

The LiDAR (light detection and ranging, LiDAR) is an active remote sensing technology that measures properties of reflected light to determine range to a distant object. And MLS system is a new generation of LiDAR devices, which are called full-waveform LiDAR systems. It is designed to digitize and to record the entire backscattered signal of each emitted laser pulse. Full-waveform data offer the opportunity to overcome many drawbacks of classical multi-echo LiDAR data [6]. The main advantage of this technique is that it provides additional information about the structure and the physical backscattering properties of the illuminated surfaces.

In the past two decades, a number of methods have been developed to delineate individual tree crowns (ITC) from airborne LiDAR data [7]. The majority of the methods are based on features of tree crowns in the canopy height model (CHM) derived from LiDAR point cloud [1, 2, 5]. For these methods, 3D points are first converted to a CHM image. Once finished the conversion, a vast amount of image processing algorithms can be used for extraction and segmentation. However, a CHM-oriented method only employs LiDAR data that describe the outer surface of tree crowns. As the equipment for LiDAR system improved, the point density of modern LiDAR data have increased. Recently some methods attempted to segment ITC directly using LiDAR 3D point clouds. Lee et al. [8] developed a clustering method to delineate individual trees in a managed pine forest directly from 3-D LiDAR data, which required a large number of training samples for a supervised learning. Li et al. [9] adopted a top-to-bottom region growing approach

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that segmented individual trees sequentially from the tallest to the shortest based on 3-D structures of tree crowns captured by LiDAR data. Jiping et al. [10] employed a spoke wheel operator to delineate the boundary of the sphere of influence. J. Reitberger et al. [11] proposed a segmentation method based on normalized cuts to extracts single trees using full waveform LiDAR data.

Despite reports of successful results, some issues remain to be resolved such as delineation of trees with complicated structures and overlapping crowns. In this paper, a method is proposed to extract individual tree crowns from MLS point cloud data. We take advantage of both the simplicity of the basic gridding idea of the CHM-oriented methods and detailed 3D data information acquired by MLS. The remainder of this paper is organized as follows. In section 2, we will discuss the detailed method used to extract individual tree crowns. Test results and their assessments are shown in section 3. At last, conclusion and discussion will be given in section 4.

2. OUR PROPOSED METHOD

Our proposed framework consisted of five steps: (1) Pre-processing period, automatically detect and remove ground points using RANSAC; (2) Vertical projection period, compress all the above ground points to image grid like in CHM but with 3D knowledge reserved; (3) Simplify this image grid and remove unqualified grid; (4) Find tree peaks in this image grid using a heuristic searching method; (5) Delineate the individual tree crowns by applying a modified watershed method.

2.1 Point cloud data pre-processing

The ground points are detected using RANSAC methods under the Point Cloud Library (PCL) framework [12]. We set the detected model type to plane and set a distance threshold which determines how close a point must be to the model in order to be considered an inlier. Our decision using RANSAC is motivated by RANSAC's simplicity and the ground are usually plane in the urban area. After the ground points are extracted like in Fig. 1, the average elevation of the ground can be calculated. We normalized the non-ground points' height value by subtracting the ground height from the points in Eq. 1:

$$z_i^{CHM} = z_i - z_i^{ground} \ (i = 1, ..., N) \tag{1}$$

where z_i^{CHM} is the height of point i in CHM, z_i is the actual height of point i, z_i^{ground} is the ground height of point i. Then the elevation value of a point indicates the height from the ground to the point. If the point is the tree top, its height value can be considered as the tree height.

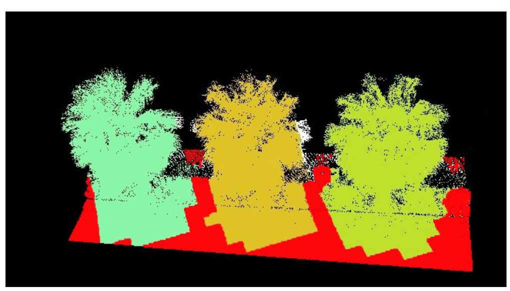


Figure 1. Ground detection result.

2.2 Vertical projection

The above ground points are then projected onto the ground surface. Like in CHM, the 2D surface is divided into grids with a predefined grid size. But unlike in CHM, where each grid has the pixel value of the max point height in the grid and the plane is then transformed into an image, the 3D information is kept for further algorithm in our model.

2.3 Filter out the unqualified grids

There are noisy and redundant points in the point cloud. To save algorithm time and obtain better results, the grids with little information must be removed. The unqualified grids are filtered out by these two criterions: (1) If the max height in this grid is less than a threshold H, all the points in this grid are removed; (2) If the density of the grid, which is computed by dividing the total point number in the grid by the grid area, is less than a threshold D, all the points in this grid are removed.

2.4 Tree peaks finding

Because the tree trunks can reflect many points, tree trunks or tree peaks are usually found in the grid with higher density than its neighborhood. Thus the peaks finding problem can be converted into a local maximal finding problem. The heuristic hill-climbing algorithm is used in the peak finding process [13]. First, the initial grid is randomly chosen. Then the neighborhood of the chosen grid is searched. A 5X5 size neighborhood is used to implement a thoroughly search. If a higher density level of the neighbors is found, the initial grid will "climb up" to the highest neighborhood. The climbing process stop until all the neighbors' density level is small than the center grid. After that, this grid is marked as one of the tree peaks, and another initial grid is chosen to restart this whole process. The algorithm is shown in Fig. 2.

Hill Climbing With Random Start Algorithm

```
loop do
    randomly select a startGrid;
    currentGrid = startGrid;
    loop do
        L = NEIGHBORS(currentGrid);
        nextHeight = -INF;
        nextGrid = NULL;
        for all x in L
        if (Height(x) > nextHeight)
            nextGrid = x;
            nextHeight = Height(x);
        if (nextHeight <= Height(x))
            //no better neighbors exist
            Store currentGrid as peak;
        currentGrid = nextGrid;
    End loop
End loop until certain iteration times met
```

Figure 2. The peak finding algorithm as proposed.

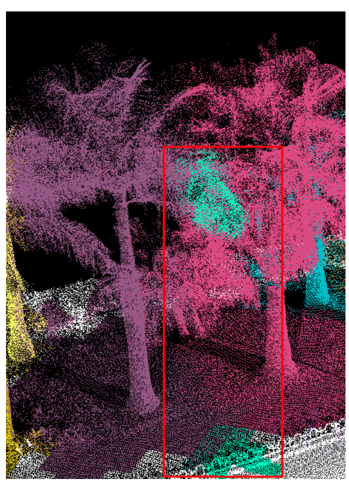


Figure 3. Invalid peak detected.

After the algorithm, all the possible locations of the tree peaks are found. However, there are still some invalid peaks in the set (Fig.3). Further criterions should be used to eliminate the unqualified peaks. (1) If more than one peak is found within a certain small radius, only the one with the highest elevation is kept. The others are some false detected peaks of the local optimal. (2) Peaks grids contain the stem points, which means these girds should have points spread out the Z axis. Grids which have points distributed only in its higher elevation and its lower elevation should be considered as non-peaks.

2.5 Delineation of individual tree crowns

After the finding of peaks, a modified watershed algorithm is employed to delineate the individual tree crowns. The peaks in the previous step are set as the seeds for water source. The workflow of the algorithm can be seen in Fig 4, in which "cur" means current.

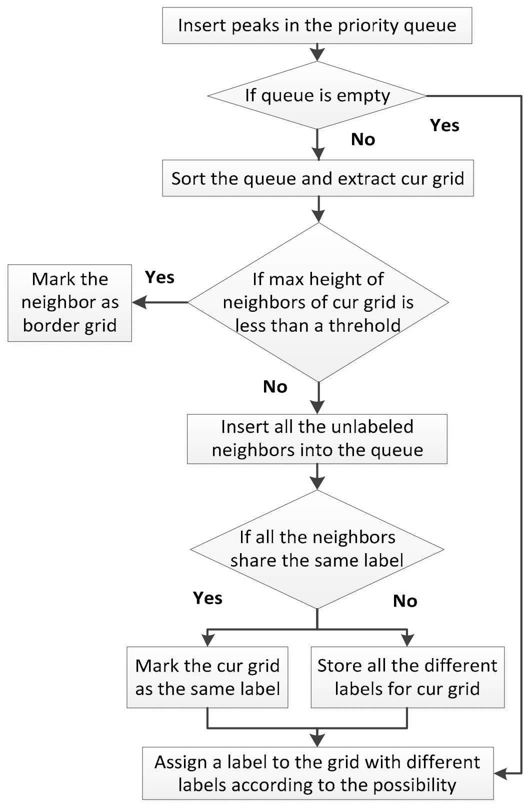


Figure 4. The workflow of the watershed algorithm.

The detail algorithm is as follows:

Step 1: The peaks grids are chosen as the seeds where the flooding shall start. Each is given a different label.

Step 2: The neighboring grids of each marked area are inserted into a priority queue with a priority level corresponding to the max height of that grid.

Step 3: The grid with the highest priority level is extracted from the queue. If the max height of the neighboring grid is less than a tree height threshold, this neighboring grid is marked as border grid. If the neighbors of the extracted grid all have the same label, then the grid is labeled with their label. If the neighbors have different labels, then record those different labels for the grid. All the non-marked neighbors that haven't been in the queue are put into the priority queue.

Step 4: Redo step 3 until the priority queue is empty.

Step 5: For the points in the grids which have several labels recorded, the label is assign to the point with a possibility related to the intensity of the point (Eq. 2&3).

$$P_i = \frac{D_i}{\sum_{t \in \text{RecordedLabels}} D_t} \tag{2}$$

and

$$D_i = \frac{1}{|d - M_i|} \tag{3}$$

Where P_i is the possibility of a point belonging to label i, D_i means the closeness of the point to label i and M_i is the mean value of the intensity of points with label i, d is the intensity value of the point. This is based on the assumption that points of the same tree share similar intensity when the laser scanned over.

3. EXPERIMENTS AND ANALYSIS

3.1 Study areas and test data

The point-cloud data used in our experiments are acquired by the RIEGL VMX-450 MLS system on Xiamen Island, China. The RIEGL VMX-450 system is the state-of-the-art MLS system in the current market. The accuracy of the scanned point-clouds is within 8 mm (1 sigma standard deviation) and the precision is 5 mm. The tested point clouds are located on Huandao Road, Xiamen Island (Fig. 5). We compare our approach to another method proposed by Ruofei Z. [14], and our performance is better than theirs.

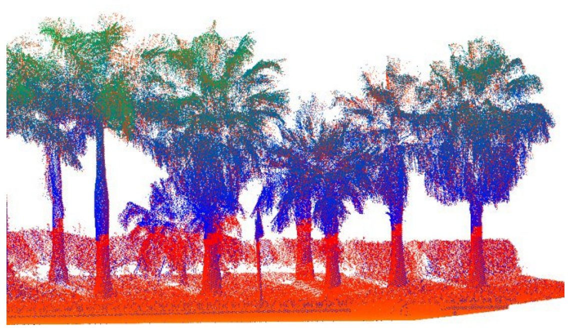


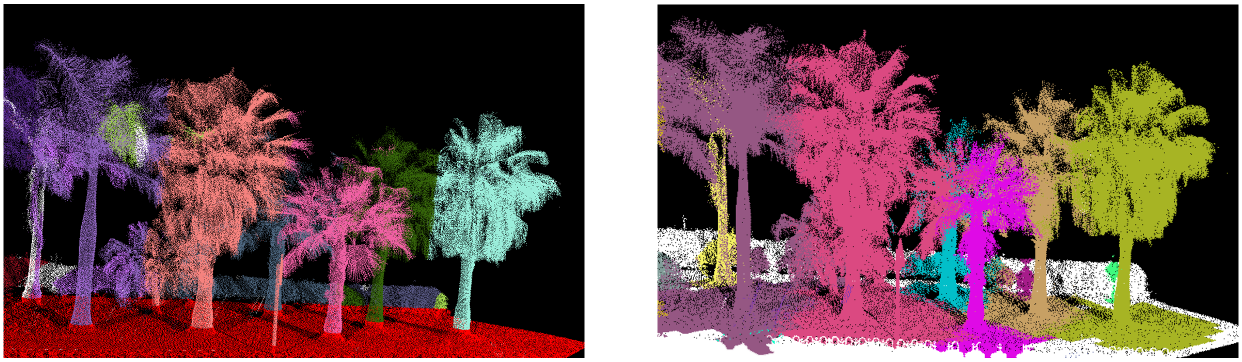
Figure 5. Overview of the tested point cloud.

3.2 Parameters setting

In our experiment, some parameters should be tuned to yield a good result. The grid size for the CHM process is set to be 0.7 meters. And the density threshold and the height elevation threshold are also set according to the point clouds. Sometimes a different grid size should be set specially for the watershed period to make the result better.

3.3 Result and performance evaluation

The extracted trees crowns are shown in Fig. 6. The detail comparison of two methods can be found in Table 1. The accuracy is calculated as the ratio of correctly delineated crowns to the total number of crowns [15]. In our result, tree stems are well detected and it gives out satisfactory result for the delineation of individual trees. In addition, our algorithm has a faster running speed.



(a) (b)

Figure 6. Extraction of individual tree crowns for overlapping trees. (a) Ruofei's method; (b) our method.

Table 1. The comparison of two methods.

Number of Points	**Point Density (points/m^2)**	**Ruofei's Method**		**Our Method**	
		Times (s)	**Accuracy (%)**	**Times (s)**	**Accuracy (%)**
975035	1729.8	49.9	67	3.04	75

4. CONCLUSION

The successful detection and delineation of individual tree crowns is critical in urban ecology, allowing for further analysis of the tree parameters. In this study, a framework is proposed to improve the delineation of individual tree crowns by exploiting the high-density of vehicle borne laser scanning point clouds. The framework takes advantage of the simplicity of CHM-oriented ITC delineation methods and applied a modified watershed algorithm. Further studies will be concentrated on the improvement of the segmentation and exploitation of the parameters that can describe the characteristics of trees in urban ecology.

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