AUTOMATED EXTRACTION OF URBAN ROADSIDE TREES FROM MOBILE LASER SCANNING POINT CLOUDS BASED ON A VOXEL GROWING METHOD

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ABSTRACT

This paper presents a new method for extracting urban roadside trees automatically from mobile laser scanning point clouds. This method mainly includes three steps. First, ground point clouds are removed by voxel-based upward growing method. Second, Euclidean distance segment method is used to cluster non-ground point clouds into certain individual objects. Then crown seeds of the initial layer is found by comparing the number of points in each layer after using the voxel modeling algorithm. Crown seeds in other layers can thereafter be detected via the upward inter-sectional analysis. Third, a crown voxel growing algorithm is used to make the crown grow in horizontal. The experimental results show that the voxel models of the individual roadside trees can be automatically and effectively extracted with our method.

***Index Terms*—** Automatic extraction, urban roadside tree, mobile laser scanning, point clouds

1. INTRODUCTION

Trees along road networks in urban areas play an important role in a city's appearance, which not only decorate the buildings but also keep the air clean. Moreover, infrastructure based city management also needs considering the tree distribution. For example, it is advisable that the trees can be pruned such that the traffic sign board can be seen clearly by the drivers and pedestrians. Likewise, in order to protect the green area and for a safer life, we should extract trees to analyze where branches or trees with potential risk may exist. Therefore, extracting trees from the point clouds catches more and more people's eyes.

In the last few years, some studies focused on the identification of trees from spectral reflectance, e.g., in [1] individual trees were isolated by comparing the red and near-infrared (NIR) reflectance. However, it was limited to the 2D outlines. In [2] the laser points were layered based on the elevation data, and then trees can be separated using the grid point density. In [3] tree crowns were detected from the projection imagery and individual trees were extracted by means of a pre-order forest traversal process through all the trees crown regions at different height levels. In [4] the laser points were classified into first, last, single and intermediate echoes, then the echo ratio (ER) of the multiple reflection was analyzed. At last, high ER values were assumed to indicate vegetation. In [5], the individual tree objects were detected by computing the geometry component statistics proportion of each object. [6] proposed a pairwise 3-D shape context to model both local and global topology structure of extracted object. Tree object was then retrieved by a similarity measurement and matching method. [7] presented a waveform representation to describe the vertical profile of tree. The deep learning model was then applied to extract the high-level feature for tree classification. [8] carried out a super-voxel based segmentation method on raw point clouds, and then a series of rules were set to merge segment as object. The tree and other objects were finally classified by a hierarchical order method.

Point clouds can retain the geometry and location information of the scanned object. Airborne laser scanning (ALS) point clouds mainly show the top boundary of the object (i.e., tree crown). Thus, the lower structures of trees (i.e. trunk, and branch) are usually hidden owing to the shading of crown. Compared to ALS data, terrestrial laser scanning (TLS) data have higher density and accuracy. Mobile laser scanning (MLS) is a more flexible, faster and more efficient technique than the TLS. MLS can collect the point clouds of the infrastructures, e.g. road and roadside trees, with high accuracy in a complex urban areas. The MLS data of trees includes both many crown points and abundant trunk points, which shows the great feasibility to extract individual trees for planting survey on an urban road environment using MLS data.

The main idea of this paper is to propose a new rapid method for automated extraction of urban road trees from MLS point clouds.

2. OVERVIEW

This paper aims at extracting the road trees from mobile laser scanning point clouds in a creative way. The workflow is demonstrated in Fig. 1 which includes ground-removing, clustering, selecting crown seed and crown seed growing. Thus, we can extract the crown.

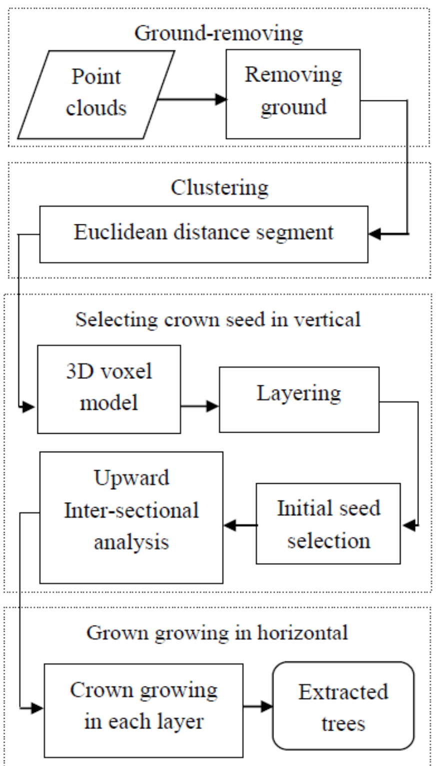
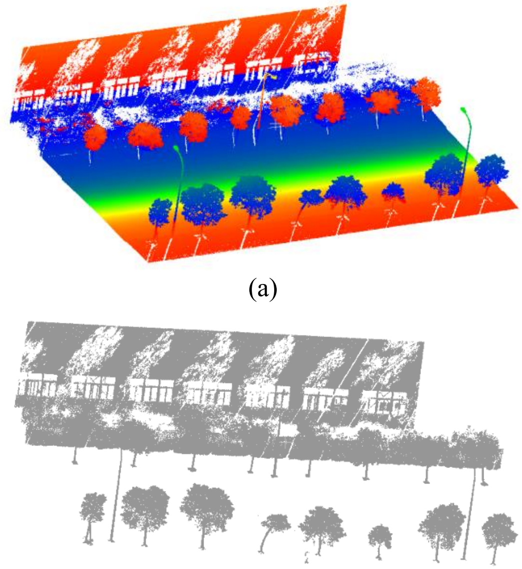


Fig. 1. Flow chart of urban road tree extraction

3. METHOD

3.1. Removing ground

The point clouds of urban road street scenes contain ground points and non-ground points. The ground removal algorithm in [9] is adopted to divide the point clouds into ground points and non-ground points. As is shown in Fig. 2(a) and 2(b), we remove the ground points of the raw data and obtain the main objects in the urban road.



(a)

(b)

Fig. 2. Removing ground: (a) raw point clouds, (b) points after ground removal

3.2. Clustering

After we have completed the ground removal, Euclidean clustering is adopted to cluster the point clouds into individual units. As shown in Fig. 3, different colors are attached to different units by their index after coding and set appropriate parameters.

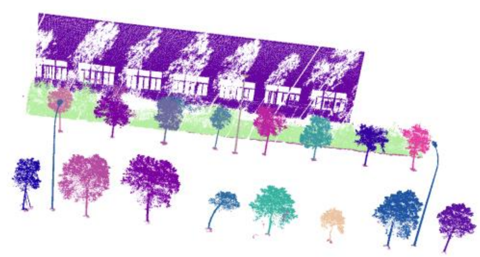


Fig. 3. Clustering for off-ground objects

3.3 Selecting crown seed

3.3.1 Voxel model and layering

We put voxel model in the clustered point clouds units with the voxel data structure just like Fig. 4. The geographical space is conceptualized and represented as a set of volumetric elements (voxels) [10]. A voxel is a block in the shape of a cuboid and its geometry is defined by length (l), width (w) and height (h). The location of a voxel in a voxel grid system is indexed by column (i), row (j) and layer (k). The clustered individual units are layered in vertical direction, and k stands for the index of each layer.

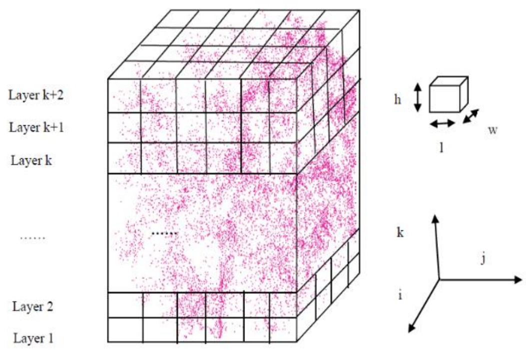


Fig. 4. Voxel modeling and layering

3.3.2. Initial seed selection

After building the voxel model and layering, we can find a feature that the most rapid increase of point amounts occurred from tree trunk to canopy in vertical layer according to Fig. 5. Other objects such as street lamps do not have this attributes. Compared with the crown of a tree, the trunk has a smaller diameter and occupies fewer voxels. In addition, the trunk is on the lower part of the tree and points of each trunk are separated spatially from points of other trunks, which shows the capacity to select an appropriate seed on a trunk for each tree. We can calculate the difference of point number between adjoined layers using the formula (1):

$$N_{i+1} - N_i = D_i \tag{1}$$

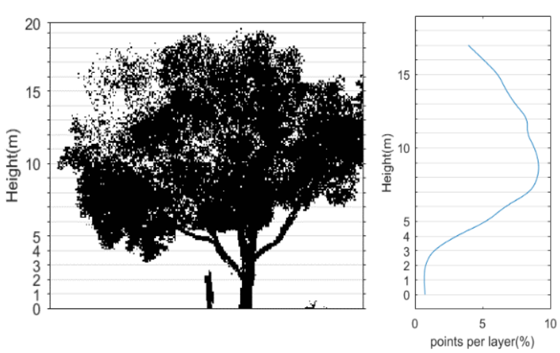


Fig 5. Point amounts of tree in each layer

where N_{i+1} and N_i are the numbers of point clouds in Layer $i+1$ and Layer i respectively. D_i means the difference between the adjacent layers. For example, it is demonstrated that the difference of point clouds amounts between layer 5 and layer 4 achieves the maximal value in Fig, 5, so we can choose the 5th layer as the initial seed layer.

3.3.3. Upward intersectional analysis

Upward cross-sectional analysis is performed to discriminate the seeds on trunks from others. As shown in Fig. 6, the analysis starts from the seeds (initial voxel groups) and traces up neighboring voxels in the upper layer to find a new voxel group until the voxel group matches the rules for crowns (Eq. (7)) or no new voxel group is found. The horizontal convex hulls of points in corresponding up-traced voxel groups in Layer i (GC_i, $i \geq$ initial) are compared by the geometric changes (GD_{up} in Eq. (5)) which is calculating by area (Eq. (2)), perimeter (Eq. (3)) and radius (Eq. (4)). The approximation degree between GC_i and the corresponding circle is calculated by Eq. (6):

$$Z_S = \frac{S(GC_{\text{initial}})}{S(GC_i)} \tag{2}$$

$$Z_l = \frac{L(GC_{initial})}{L(GC_i)} \tag{3}$$

$$Z_r = \frac{radius(GC_{initial})}{radius(GC_i)} \tag{4}$$

$$GD_{up} = \alpha Z_s + \beta Z_l + \gamma Z_r \tag{5}$$

$$Z_{area} = \frac{S(GC_i)}{\pi \times (radius(GC_i))^2} \tag{6}$$

where $\alpha + \beta + \gamma = 1$ and $\alpha = 2\beta = 2\gamma = 0.5$

Based on these calculations, a crown is distinguished by the following rules:

$$radius(GC_i) > R_{crown} \;\&$$
$$Z_{area} > S_{crown} \;\&$$
$$GD_{up} < H_{up} \tag{7}$$

When a voxel group satisfies the above rules, canopy is deemed to have been found.

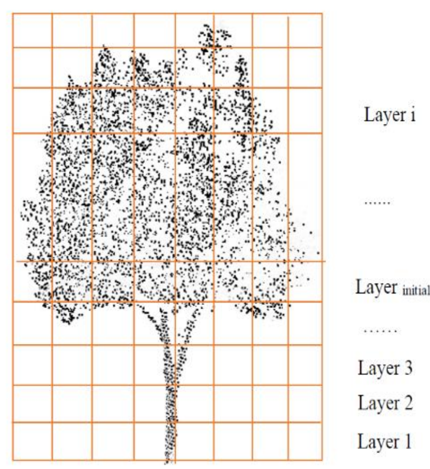
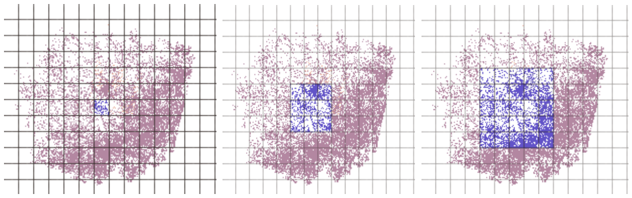


Fig 6. Upward intersectional analysis

3.4. Crown growing

Taking all the voxels of a canopy layer out of the voxel space, the voxels of the layer can be regarded as pixels of an image shown in Fig.7. Voxels in blue are expanded in horizontal direction with 8-neighborhood growing from the seed voxels in the current layer. Only voxels with enough points are used to growing.



(a) (b) (c)

Fig. 7. Crown growing

The new crown voxels in blue are regarded as a seed voxel to continue the horizontal 8-neighborhood growing. Once no new crown voxel in the current layer is found, the upward growth is implemented again. When several trees are presented in a cluster, tree growing is performed one by one in the current layer followed by the next layer. These repeating steps stop until the top crown layer has finished growing. When all the process is completed, we label certain color to potential crown layer and detect its trunk in downward direction, which is similar to the upward intersection analysis. Then, we can extract individual trees.

4. RESULTS

This proposed method was tested on the point clouds of urban road scenes with complex objects on Haicang district, Xiamen, China. The experiment datasets used in this paper were acquired by a RIGEL VMX-450 system. The results are shown in Fig. 8. Road surface, grass, buildings and street lamps have been ruled out, crown layers is labeled in green. Urban road tree are extracted successfully from the point cloud data.

Fig. 8. Results of Extraction

In our dataset, 68 independent objects and 5 overlapping objects were extracted. The independent objects consist of 43 road trees and 25 non-tree individuals. The detected positives (DP) are the number of trees which are correctly extracted. The missed positives (MP) are the number of missed tree after extraction. Likewise, we introduce DN (detected negatives) and MN (missed negatives) to test the correlative results of objects that are not trees.

Table 1. Results of extraction

DP	MP	DN	MN	Score
41	2	21	4	93.18%

In Table 1, the evaluation equation for the data set was established below.

Precision: $P = DP/(DP + MP)$, Ratio of Recall: $R = DP/(DP + \mathrm{MN})$, Score: $S = 2PR/(P + R)$

To conclude, we can know that $P = 95.35\%$, $R = 91.11\%$, $S = 93.18\%$ after calculation. The visual results are demonstrated in Fig. 7. The roadside trees are extracted from the urban road scenes successfully. On the contrary, the road, buildings, hedge, cars, and traffic signs are removed.

5. CONCLUSION

Extraction roadside trees automatically brings convenience to environmental monitoring and biomass estimation. The results of our proposed algorithms show the feasibility to detect and extract trees. However, a very few of point clouds on the margin of crown layer have not been attached color, we will improve it during the future work.

ACKNOWLEDGEMENTS

This work was supported by National Natural Science Foundation of China (Grant No. 61601392) and ATR Fund (Grant No. 9140C800401150C80339).

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