COMPARISON OF INDIVIDUAL TREE SEGMENTATION BASED ON ALS POINT CLOUD

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ABSTRACT: This paper studies four individual tree segmentation methods: the watershed algorithm, Point cloud-based segmentation, Dalponte's method and Silva's method, and analyzes the accuracy. The result showed that the four segmentation methods used to segment individual trees have relatively high overall accuracy (overall accuracy F=0.610-0.820), Dalponte's method and Silva's method has higher accuracy. The CHM resolution affects the segmentation result of CHM based methods, the threshold of point cloud-based segmentation is different based on the point cloud data. It would be better to develop an adaptive threshold method.

1 INTRODUCE

Airborne Laser Scanning (ALS) is an effective technology to support forest inventory and research (Wulder et al., 2012). ALS point clouds can provide rich information on forest structure (such as: canopy height, canopy layering, volume, breast diameter and so on) Individual tree segmentation is the foundation of many forest applications including tree structures, tree species classification and so on. The main difficulty comes from the complex spatial structure of trees, which includes overlap of canopy, heterogeneity of canopy shape (Parkan and Tuia, 2015). Depending on the point cloud data used, most of the current individual tree segmentation algorithms can be divided into three categories: raster, vector, mixed. One is to generate a raster surface model (CHM) based on the lidar point cloud data, and then perform an individual tree segmentation(Chen et al., 2006; Dalponte and Coomes, 2016; Silva et al., 2016). The second is to use the normalized LiDAR point cloud data to cluster according to the spatial structure relationship and attribute information between LiDAR point clouds, and directly perform single tree segmentation(Li et al., 2012).

Most of the above studies only discussed the effect of a certain individual tree segmentation method. Thus, based ALS point cloud, this paper compares the individual tree segmentation algorithms of the watershed algorithm, point cloud-based segmentation, Dalponte' method and Silva' method. Provide reference for forest inventory.

2 METHODOLOGY

2.1 Point Cloud-based Segmentation

The point cloud is segmented from the high to low, and a threshold is set to exclude the point cloud whose horizontal distance from the target individual treetop is greater than the threshold. As shown in Figure 1, tree 1 is the target tree, and point A is the vertex of tree 1, point B is the vertex of tree 2, and the point cloud of tree 1 is excluded for d_{AB} is greater than the specified threshold. Secondly, point C belongs to tree 1, for d_{AC} is less than d_{BC} and d_{AC} is less than the threshold. Point D belongs to tree 2, because d_{CD} is greater than d_{BD}. Though iterative judgment, the individual trees are divided(Li et al., 2012).

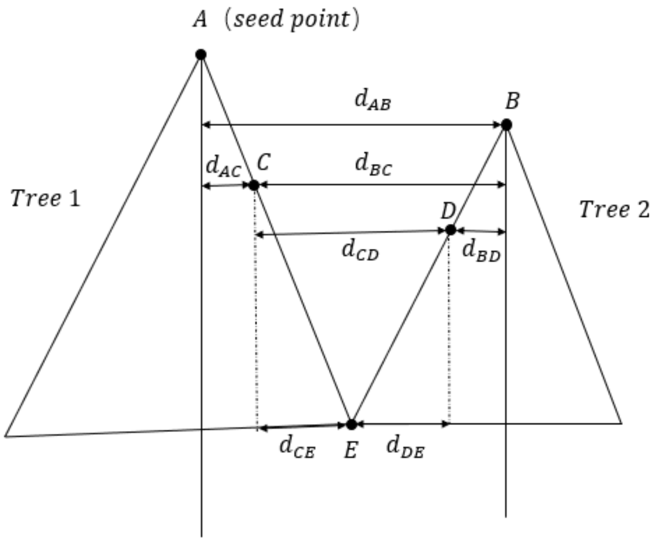

Figure 1 Point Cloud-based Segmentation (Li et al., 2012)

2.2 Watershed Algorithm

The watershed algorithm is a mathematical morphology algorithm similar to the immersion process. The grey value in the CHM image corresponds to the height, and then the grey value is inverted. There are some local minimum points in the image. Suppose a hole is punched at each minimum point, and then water is injected from the minimum point. The water gradually submerged from the lowest point of the image, eventually forming a basin. As the water level in the reservoir rises, the water surface at different minimums will converge. At this time, a dam will be built between the two reservoirs. After the process is over, the area where each minimum point is located will be surrounded by corresponding dikes, and the collection of these dikes forms a watershed. The dam is the boundary of image segmentation, and the stagnant basin is the segmentation region(Popescu and Wynne, 2004). The watershed algorithm is used to determine the tree crown boundary, and then the local maximum is found in each segment as the treetop(Wulder et al., 2000).

2.3 Dalponte's Method

This method finds the local maximum in the CHM image. The local maximum is the top of the tree, and then a single tree crown is grown near the local maximum using the decision tree method. Firstly, a low-pass filter was applied to the CHM to smooth the surface and reduce the number of local maxima. Secondly, a circular moving window was used to locate the local maximum. Thirdly, each local maximum is marked as a seed point where the canopy can grow. Finally, extract the single tree point from each area(Dalponte and Coomes, 2016).

2.4 Silva's Method

This method uses a local maximum algorithm to search for treetops in CHM through a moving window with a fixed treetop window size. If the treetop height is greater than the threshold, the point is a treetop. Then, a variable radius canopy buffer is used to define the initial canopy area. The centroid Voronoi mosaic method is used to segment the data to isolate each individual tree polygon. Finally, the tree crown is calculated by delimiting the boundaries of the grid cells belonging to each tree(Silva et al., 2016).

2.5 Error Assessment

Based on the number of true positives (n_{TP}), false negatives (n_{FN}), false positives (n_{FP}), common segmentation metrics such as recall (r), precision (p) and F-score (F) can be calculated:

$$\begin{cases} r = \frac{n_{TP}}{n_{TP}+n_{FN}} \\ p = \frac{n_{TP}}{n_{TP}+n_{FP}} \\ F = \frac{2*(p*r)}{p+r} \end{cases} \tag{1}$$

3 RESULTS AND ANALYSIS

The ALS point cloud data are from the NEWFOR website (http://www.newfor.net)(Eysn et al., 2015). Figure 2 shows the original ALS point cloud, the ground point was filtered by CSF(Zhang et al., 2016) as shown in Figure 3. Then the point cloud was normalized(Figure 4), The 0.5m CHM(Figure 5) was generated based on the point cloud. Figure 6-9 show the the segmentation results. Figure 10 shows the tree position. Table 1 shows the error assessment.

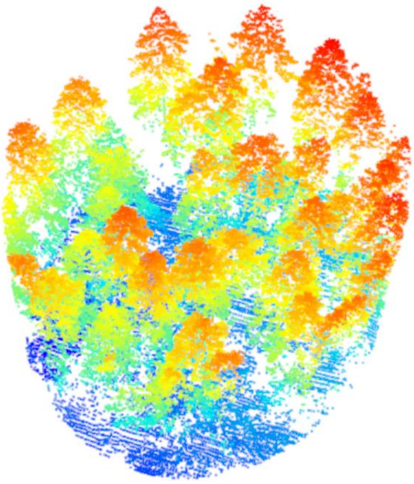

Figure 2 ALS Point Ploud

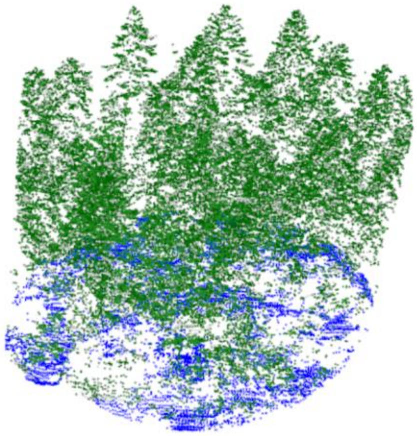

Figure 3 Ground Point Filtering

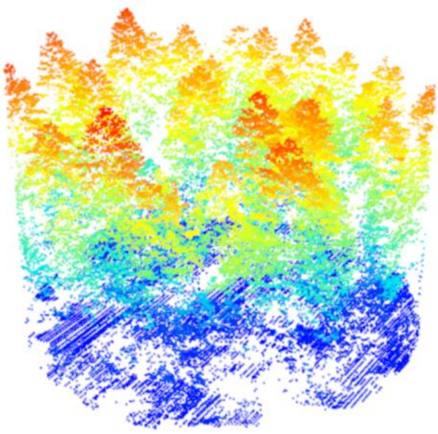

Figure 4 Normalized Point Cloud

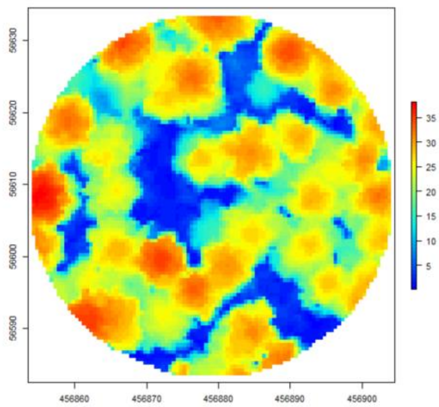

Figure 5 CHM

Figure 6 Watershed Algorithm

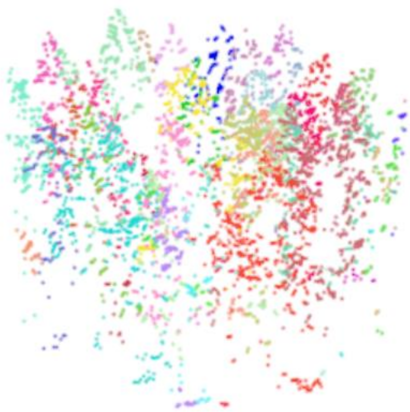

Figure 7 Li’s Metho

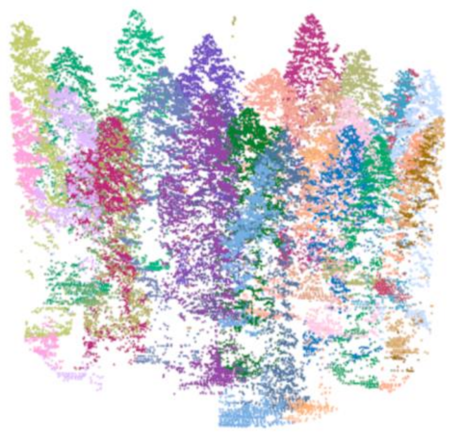

Figure 8 Dalponte's Method

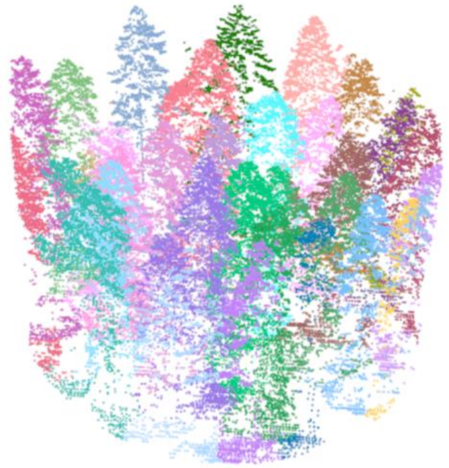

Figure 9 Silva's Method

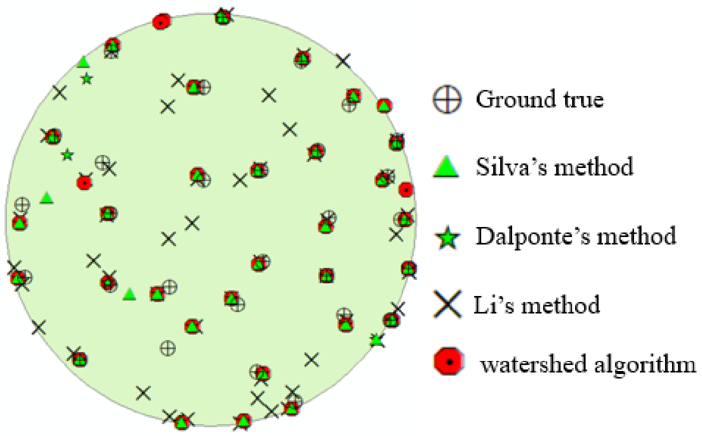

Figure 10 Tree Position

Table 1 Error Assessment

	d_{AB}/R_{CHM} (m)	r	p	F
Li's method	1.5	1.000	0.439	0.610
	2.0	1.000	0.527	0.690
	2.5	1.000	0.558	0.716
watershed algorithm	0.3	0.931	0.675	0.783
	0.5	0.897	0.743	0.813
	0.8	0.793	0.821	0.807
Dalponte's method	0.3	0.828	0.774	0.800
	0.5	0.862	0.781	0.820
	0.8	0.862	0.758	0.807
Silva's method	0.3	0.828	0.75	0.787
	0.5	0.862	0.781	0.820
	0.8	0.828	0.727	0.774

The CHM resolution affect the segmentation result of CHM based methods. The result of Li's method is not very good, the reason may be the threshold do not match the point cloud. it is necessary to adjust parameters of the individual tree segmentation algorithm to make it more suitable for the point cloud.

4 CONCLUSIONS

This paper studies four individual tree segmentation methods: the watershed algorithm, Point cloud-based segmentation, Dalponte's method and Silva's method, the recall, precision and F-score was calculated to assess the result. The result showed that the four segmentation methods used to segment individual trees have relatively high overall accuracy (overall accuracy F=0.716-0.820). The CHM resolution affects the segmentation result of CHM based methods This paper provides a useful reference for forestry inventory.

REFERENCES

Chen, Q., Baldocchi, D., Gong, P. and Kelly, M., 2006. Isolating Individual Trees in a Savanna Woodland using Small Footprint LIDAR data. Photogrammetric Engineering & Remote Sensing, 72(8), pp. 923-932.

Dalponte, M. and Coomes, D.A., 2016. Tree - centric mapping of forest carbon density from airborne laser scanning and hyperspectral data. Methods in Ecology and Evolution, 7(10), pp. 1236-1245.

Eysn, L. et al., 2015. A Benchmark of Lidar-Based Single Tree Detection Methods Using Heterogeneous Forest Data from the Alpine Space. Forests, 6(12), pp. 1721-1747.

Li, W., Guo, Q., Jakubowski, M.K. and Kelly, M., 2012. A New Method for Segmenting Individual Trees from the Lidar Point Cloud. Photogrammetric Engineering & Remote Sensing, 78(1), pp. 75-84.

Parkan, M. and Tuia, D., 2015. Individual tree segmentation in deciduous forests using geodesic voting, 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), pp. 637-640.

Popescu, S.C. and Wynne, R.H., 2004. Seeing the trees in the forest: using LiDAR and multispectral data fusion with local filtering and variable window size for estimating tree height. Photogram-metric Engineering & Remote Sensing, 70(5), pp. 589-604.

Silva, C.A. et al., 2016. Imputation of Individual Longleaf Pine (Pinus palustris Mill.) Tree Attributes from Field and LiDAR Data. Canadian journal of remote sensing, 42(5), pp. 554-573.

Wulder, M., Niemann, K.O. and Goodenough, D.G., 2000. Local Maximum Filtering for the Extraction of Tree Locations and Basal Area from High Spatial Resolution Imagery. Remote Sensing of Environment, 73(1), pp. 103-114.

Wulder, M.A. et al., 2012. Lidar sampling for large-area forest characterization: A review. Remote Sensing of Environment, 121, pp. 196-209.

Zhang, W. et al., 2016. An Easy-to-Use Airborne LiDAR Data Filtering Method Based on Cloth Simulation. Remote Sensing, 8(6), pp. 501.