ESTIMATION OF FOREST TREES DIAMETER FROM TERRESTRIAL LASER SCANNING POINT CLOUDS BASED ON A CIRCLE FITTING METHOD

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ABSTRACT

In forest monitoring and management, any rational decision needs to be based on forest parameters. The diameter at breast height (DBH) of a tree is considered to be the most significant parameter among them. This paper presents a novel method for extracting tree stems and estimating DBH of trees in a forest environment from 3D point clouds data acquired by a terrestrial laser scanning (TLS) system. In the proposed method, a downward-growing algorithm is used to extract individual tree stems and DBH of trees are estimated by the circle fitting algorithm. This proposed method can avoid errors caused from tilted trees by estimating a plane perpendicular to the tree stem. With this method, 17 trees were extracted from single-scan point cloud data consisting of 21 trees. The estimated DBH had a bias of 0.38 cm and a root mean squared error of 1.76 cm. These experiment results show the feasibility of the proposed method.

Index Terms—Terrestrial laser scanning, 3D point clouds, stem detection, DBH, forestry

1. INTRODUCTION

The volume of wood is an important key variable in forest inventory. This key variable is usually derived from several forest structural parameters such as diameter at breast height (DBH), height and crown of trees. At all of these forest parameters measurements, accurate measurement of DBH is a critical step. Small changes in DBH will lead to a significant difference in volume due to the volume of wood is in direct proportion to the square of the radius of trunks. The traditional way of acquiring DBH is derived from the circumference of trunks, while the circumference is manually measured with a tape measure. Only a small part of all trees in the forest can be measured because it is time-consuming and labor-intensive for acquiring DBH of trees by traditional measure ways. Therefore, the research and application value of acquiring DBH of trees automatically is obvious.

Terrestrial laser scanning (TLS) has been established as a non-destructive surveying technology that allows capturing 3D point clouds with a high precision and spatial resolution [1]. These millions of 3D points record most of the forest information we need in millimeter-level detail [2]. An automatic data processing method is needed to get DBH of trees from 3D point clouds.

There are not only tree stems in original point cloud of the forest scenes, but also stones, low vegetation and leaves. Before acquiring DBH of trees, detection of trees or stems in point clouds is an indispensable procedure. In [3], the cluster algorithm and statistical component features of each object were used to detect trees. In [4], the individual tree was extracted based on the density of the points projected onto the X-Y plane. In [5], the Hough transformation was used on projected point clouds to detect tree stems and a modified RANSAC method is used to compute diameters of the tree. Researchers in [6] and [7] proposed a two-layer projection approach to determine the location of each tree and cylinder fitting and growing to extract stem of the tree. Before cylinder fitting, the RANSAC was simply applied to reduce noise. The following two steps were presented in [8] to acquire DBH of trees: (1) developing a 3D template which has a leaning angle to detect tree stem that extant upwards from the ground surface, and (2) using a circle fitting algorithm to seek the circle center and radius from projected points. A clustering algorithm based on the horizontal scan angle and the range as well as an adaptive circle-ellipse fitting method based on the point clouds transects were presented in [9] to extract the DBH of trees from single-scan point clouds. The Fourier series curve approximation combined with the circle fitting was proposed in [10] for modeling stem cross-section shapes, while tree stems were manually identified from the multiple-scan point clouds.

The main idea of this paper is to propose a new method for automated detection of trees and measurement of DBHs from 3D point clouds. The method was evaluated on single-scan point cloud data acquired by a RIEGL VZ-1000 TLS system.

2. FRAMEWORK

This paper aims at measuring DBH of trees automatically from the 3D point cloud. The workflow is demonstrated in Fig. 1 which includes four steps: data pre-processing, noise filtering, detecting stems and measuring DBH. The outputs of this workflow are DBH and location of every tree.

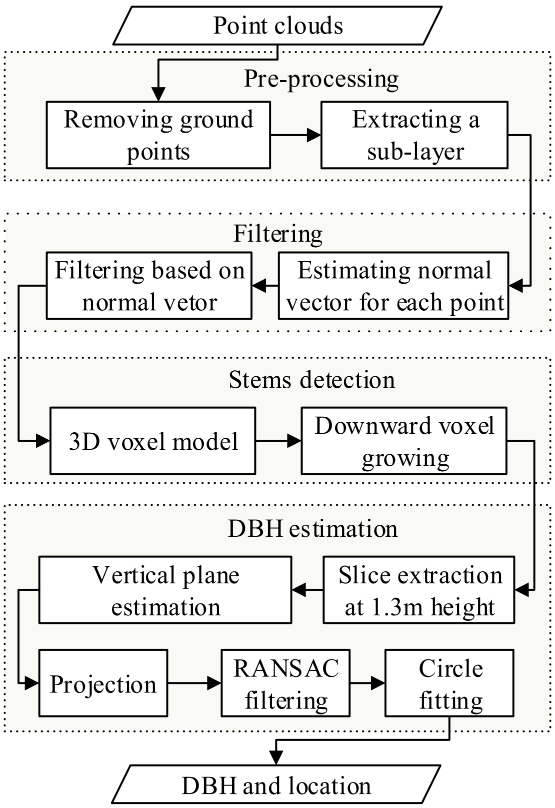

Fig. 1. Workflow of DBH estimation

3. METHOD

3.1. Data pre-processing

The 3D point clouds acquired by the TLS system consist of a lot of ground points. These ground points will take a large amount of computation time and memory space. Therefore, the ground removal algorithm used in [11] is adopted to remove ground points from the raw point clouds. The purpose of this paper is to determine the location of the stems and measure the DBH (1.3 m high above the ground) of stems. Theoretically, a height threshold of 2.5 m is used to remove those off-ground points higher than 2.5 m above ground. Fig. 2(b) shows off-ground points after ground points removal, Fig. 2(c) shows the off-ground points lower than 2.5 m above ground.

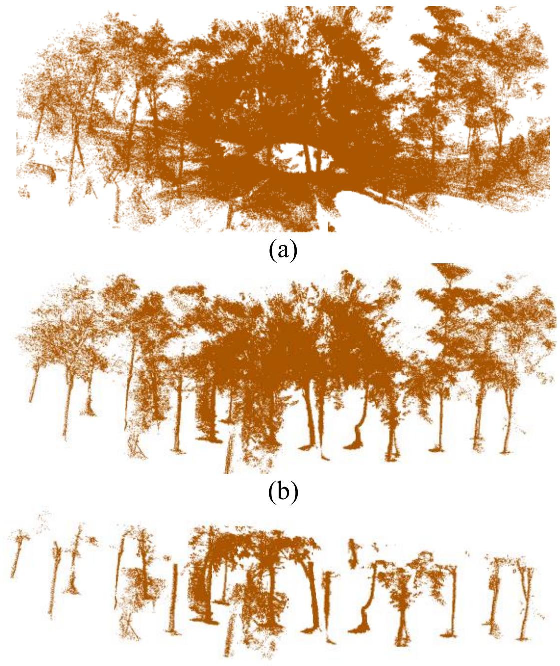

Fig. 2 Data pre-processing: (a) raw point clouds, (b) off-ground points, and (c) off-ground points lower than 2.5 m above ground

3.2. Filtering

In [12], one point is preliminarily identified as a stem point if it is of low variance in one direction in a local coordinate system and has a close-to-horizontal normal vector in the real-world coordinate system. The results of [12] show that this approach is valid. Inspired by this approach, non-stem points are removed from the sub-layer points based on the normal vector Z component value. Tree stems are almost upright in spatial, the normal vectors of points belonging to a stem have a Z component with a small absolute value such as $\boldsymbol{P}_2$ and $\boldsymbol{V}_2$ in Fig. 3. While the absolute values corresponding to the points on tree crowns, bushes, leaves etc. are higher than a threshold set by experience. These points will be filtered out such as $\boldsymbol{P}_1$ in Fig. 3.

The normal vector of each point is estimated from the spatial position of k nearest points around a point. A plane is fitted to neighboring k points to estimate the normal vector. The solution for fitting plane is to analyze the eigenvector and eigenvalues of a covariance matrix $\boldsymbol{C}$ created from these k points. The eigenvector of $\boldsymbol{C}$ corresponding to the smallest eigenvalue will be approximate of a normal vector. The covariance matrix $\boldsymbol{C}$ is:

$$\boldsymbol{C} = \frac{1}{k}\sum_{i=1}^{k}(\boldsymbol{p}_i - \overline{\boldsymbol{p}})(\boldsymbol{p}_i - \overline{\boldsymbol{p}})^T \quad (1)$$

where $\boldsymbol{p}_i = (x_i, y_i, z_i)$ and $\overline{\boldsymbol{p}} = \frac{1}{k}\sum_{i=1}^{k}\boldsymbol{p}_i$.

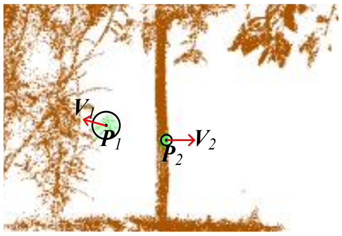

Fig. 3 Illustration of filtering

3.3. Stems detection

Almost all of the points contained in the sub-layer are belonged to tree stem after filtering. These retained points are divided into several voxels at a predefined resolution of $l \times w \times h$ as shown in Fig. 4. A voxel is a small block in the shape of a cuboid. The points number in a voxel is assigned to the corresponding voxel. The voxels and points numbers are denoted as v_{ijk} and n_{ijk}, respectively, $i \in [1, L]$, $j \in [1, W]$, $k \in [1, K]$, where L, W and K are the voxels numbers along X-, Y-, and Z-axis, respectively. A downward-growing method is used to detect tree stems in the voxel structure point clouds.

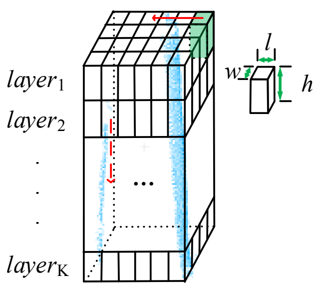

Fig. 4 Cuboid and downward-growing

We firstly search the voxel whose point number n_{ijk} is more than a threshold N_{thres} in $layer_1$ (the topmost). Once a satisfied voxel v_{ijk} is sought, it is added into point cloud $tree_l$ (the lth tree stem). The satisfied neighbor voxels are also added into $tree_l$ by a region growing algorithm. The downward-growing algorithm under the same condition is used to grow all voxels belonging to this stem from those voxels which have not been added into $tree_l$. After all voxels in $layer_1$ have been searched or grown, these steps will be repeated in those voxels in next layer which have not been grown. This stem growing algorithm will stop in the bottom layer, when extracting all suspected tree stems. Stems whose heights are small than a threshold will be removed from the suspected stems, because they should be bushes or stones rather than tree stems.

3.4. DBH estimation

All tree stems have been extracted and separated from single-scan point clouds completely. For each tree stem, a slice with a thickness d is cut out of the stem at a height of 1.3 meters above the ground as shown in Fig. 5 (a). The normal vector of each point is used to estimate a plane perpendicular to the stem. The cross product of normal vectors of two different points on the stem is close to the normal vector ($\boldsymbol{v}_s$) of the estimated plane. So the normal vector $\boldsymbol{v}_s$ can be computed by

$$\boldsymbol{v}_s = Nor\left(\sum_{i=1}^{M}\sum_{j=1}^{M}(\boldsymbol{v}_i \times \boldsymbol{v}_j)\cdot sgn(Z_{ij})\right) \tag{2}$$

where M is the number of points in the point clouds, $\boldsymbol{v}_i$ is the normal vector of point i. $sgn()$ is the sign function, Z_{ij} is the Z component of $\boldsymbol{v}_i \times \boldsymbol{v}_j$ and $Nor(\boldsymbol{v})$ represents the normalizing vector $\boldsymbol{v}$. It is easily to get a plane perpendicular to the stem with normal vector $\boldsymbol{v}_s$.

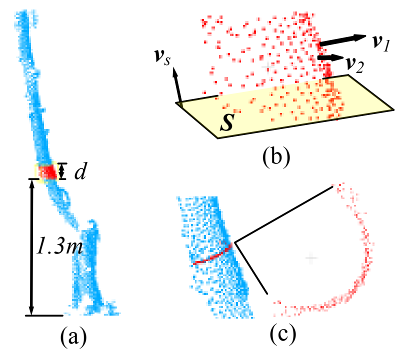

Fig. 5 (a) A point cloud (red), (b) perpendicular plane estimation, and (c) projected points (red)

All points are projected onto the estimated plane. Comparing to [9], this is an easier method to avoid the errors result from the tilted trees. The elevation view and vertical view of projected points are shown in Fig. 5(c). There may be some noise points reflected by adventitious roots or tender shoots among projected points. These noise points can be filtered out through the RANSAC algorithm with circle model. After filtering, a circle fitting method is used on projected points to acquire the location and DBH of tree stems.

4. RESULTS AND DISCUSSION

In the experiments, the raw TLS points clouds used in this study showed in Fig. 2(a) were acquired in the Siming district of Xiamen by a RIEGL VZ–1000 TLS system. The acquired point clouds contain 21 trees. Fig. 6 shows 17 tree stems that were automatically extracted by the proposed method. According to the observations, two missed trees were obscured, and the others had a very low point density because they were too far from the scanning position of the TLS system.

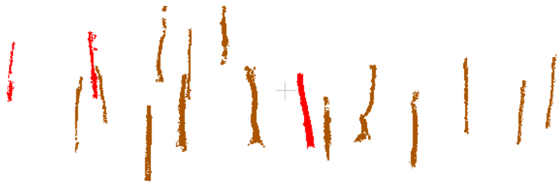

Fig. 6 Extracted stems

TABLE 1. Estimated DBHs and field-measured DBHs (cm)

Estimated	Field	Error	Estimated	Field	Error
15.72	13.69	2.03	14.84	15.61	-0.77
15.54	15.92	-0.38	13.11	14.01	-0.90
10.26	8.47	1.79	15.53	14.80	0.73
12.04	13.50	-1.46	13.75	13.80	-0.05
15.51	15.11	0.40	17.40	15.31	2.09
20.06	15.76	4.30	11.39	11.49	-0.10
10.95	13.40	-2.45	18.50	15.60	2.90
13.33	14.01	-0.68	15.55	14.90	0.65
11.47	13.05	-1.58			

Table 1 lists those estimated DBHs and the field-measured DBHs. The bias, root mean square error (RMSE) and RMSE (%) are calculated to evaluate the estimation accuracy.

$$Bias = \frac{1}{k}\sum_{i=1}^{k}(d_i - \hat{d}_i) \tag{3}$$

$$RMSE = \sqrt{\frac{1}{k}\sum_{i=1}^{k}(d_i - \hat{d}_i)^2} \tag{4}$$

$$RMSE\,(\%) = 100 \times \frac{\mathrm{RMSE}}{\bar{d}} \tag{5}$$

where d_i is the estimated value and $\hat{d}_i$ is the reference value; $\bar{d}$ denotes the mean of the reference value and k represents the number of extracted trees.

The DBHs were estimated with a bias of 0.38 cm and an RMSE of 1.76 cm (12.18%). While the RMSE of DBHs estimation was 1.98 cm for only using circle fitting on points projected onto the horizontal plane. The improvement of these results is mainly coming from the more accurate DBHs estimating for some tilted trees (e. g. the red ones in Fig. 6). It is shown that the proposed method achieved a better result.

5. CONCLUSION

In this paper, we present an automated method for extracting tree stems and measuring DBH. As the cross product of normal vectors, to estimate the plane which is perpendicular to tree stem, can avoid errors caused by tilted trees. In test data, 17 trees were detected correctly, and 4 trees were missed. The reasons for missing trees demonstrated that the density of point cloud and complexity of forest affect the accuracy of trees detection. The bias of 0.38 cm could be caused by the noise points reflected from knots on tree stem.

The results of tree stems extraction and evaluation imply that the proposed method is able to acquire DBH of trees in the forest. Processing the point clouds data with voxel structure takes the most time, so faster trees extraction method in the complex forest will be father studied in the future work.

ACKNOWLEDGEMENTS

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REFERENCES

[1] M. Kunz, C. Hess, and P. Raumonen, et al, "Comparison of wood volume estimates of young trees from terrestrial laser scan data," *iForest – Biogeosci. Fores.*, vol. 10, no. 2, pp. 451-458, 2017.

[2] X. Liang, V. Kankare and J. Hyyppä, et al, "Terrestrial laser scanning in forest inventories," *ISPRS J. Photogramm. Remote Sens.*, vol. 115, pp. 63-77, 2016.

[3] P. Huang, Y. Chen, and J. Li, et al, "Extraction of street trees from mobile laser scanning point clouds based on subdivided dimensional features," *In: IGARSS 2015*, pp. 557-560, 2015.

[4] X. Zou, M. Cheng, and C. Wang, "Tree classification in complex forest point clouds based on deep learning," *IEEE Geosci. Remote Sens. Lett.*, vol. 14, no. 12, pp. 2360-2364, 2017.

[5] K. Olofsson, J. Holmgren and H. Olsson, "Tree stem and height measurements using terrestrial laser scanning and the RANSAC algorithm," *Remote Sens.*, vol. 6, no. 5, pp. 4323-4344, 2014.

[6] D. Wang, M. Hollaus, and E. Puttonen, et al, "Automatic and self-adaptive stem reconstruction in landslide-affected forests," *Remote Sens.*, vol. 8, no. 12, p. 974, 2016.

[7] D. Wang, M. Hollaus, and E. Puttonen, et al, "Fast and robust stem reconstruction in complex environments using terrestrial laser scanning," *ISPRS Archives*, vol. -3, pp. 411-417, 2016.

[8] Z. Xi, C. Hopkinson and L. Chasmer, "Automating plot-level stem analysis from terrestrial laser scanning," *Forests*, vol. 7, no. 12, p. 252, 2016.

[9] G. Bu and P. Wang, "Adaptive circle-ellipse fitting method for estimating tree diameter based on single terrestrial laser scanning," *J. Appl. Remote Sens.*, vol. 10, no. 2, p. 026040, 2016.

[10] D. Wang, V. Kankare, and E. Puttonen, et al, "Reconstructing stem cross section shapes from terrestrial laser scanning," *IEEE Geosci. Remote Sens. Lett.*, vol. 14, no. 2, pp. 272-276, 2017.

[11] Y. Yu, J. Li, H. Guan, C. Wang and J. Yu, "Semiautomated extraction of street light poles from mobile LiDAR point-clouds," *IEEE Trans. Geosci. Remote Sens.*, vol. 53, no. 3, pp. 1374-1386, 2015.

[12] X. Liang, V. Kankare, and X. Yu, et al, "Automated stem curve measurement using terrestrial laser scanning," *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 3, pp. 1739-1748, 2014.