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Stumpage Forestry Data Mining based on 3D Laser Point Cloud

***Abstract**. Terrestrial laser scanner (TLS) was used to obtain stumpage point cloud data. Firstly, we used the ball neighbourhood combining with a uniform grid method to represent the spatial topology construction of the point cloud, thereby reduced the amount of calculation. Secondly, we used Hough transform to calculate timber volume and abandoned branches and leaves interference according to different depth circular centers continuity. Thirdly through calculating the point cloud features, such as normal vector, curvature, bending, etc, then automatically located the secondary branches position; Finally, comparing with the really measurement trees parameters; the effectiveness of our proposed method is proved.*

***Streszczenie.** W artykule przedstawiono wyniki prac dotyczących wykorzystania laserowego skanera przestrzeni (ang. Terrestrial Laser Scanner – TLS) do uzyskania danych dotyczących ilości drewna na danym terenie, w celu ustalenia opłaty wycinkowej. W tworzeniu struktury przestrzennej chmury danych, wykorzystano metodę siatki jednolitej w połączeniu z kulistą formą otoczenia, co dało ograniczenie liczby obliczeń. W drugim etapie zastosowano transformację Hougha, do obliczenia ilości drewna, wolnych gałęzi i zakłóceń wywołanych liśćmi, a na koniec wyznaczono parametry chmury danych, jak wektor normalny, krzywizna, zagięcia itp. Porównanie z danymi rzeczywistymi potwierdza skuteczność metody. **(Wykorzystanie laserowego skanera 3-D w analizie danych dotyczących wyznaczania opłat za wycinkę drewna)**.*

Keywords: Point cloud data, Forestry parameters, Computer analysis.
Słowa kluczowe: dane chmury punktów, współczynniki zalesienia, analiza komputerowa.

Introduction

The forest has an irreplaceable status in regulating the earth's environment for human survival and slowing down global environmental degradation trend, forest mensuration and forestry information research become an important issue in recent years, how to solve the forest tree fine measurement and provide an effective way is the main task of forestry management. Traditional mechanical tree measurement tools have low efficiency, and obtained measuring data with single form and poor precision; Trees measurement using optical method will be influenced by the occlusion and illumination, it has strict requirements in image acquisition angle and accuracy camera parameters, although using ultrasonic sensor array for tree measurement can get three-dimensional lattice image data of tree canopy, but only obtain tree surface data and can't get canopy internal structure information. Terrestrial Laser Scanner (TLS) using laser ranging principle, be able to record true three-dimensional information of the space objects. Many scholars have used this technology in recent years [1, 2, 3]. By means of laser scanner technology, we obtained real tree 3D point cloud data, and combined with the latest computer graphics and image theory to automatically extract forest parameters, then can describe the inherent laws of trees growth variation, and show the real biomass information by 3D visualization method.

We used Leica laser scanner to scan a stumpage in campus from three different viewpoints, and realized point-clouds data registration to obtain the complete 3D tree model. tree 3D point cloud data as shown in Fig. 1, as can be seen from the figure, the tree with extremely complex morphology, so how to automatically obtain key forest parameters from the complex three-dimensional model is a problem to be solved in this paper.

This article is committed to mining the stumpage important forest parameters from the TLS point cloud data, Firstly point cloud data topological structure based on the grid and sphere neighbourhood is introduced, and according to the Hough transform to obtain main stem section circle centers, then trees main skeleton is extracted; Secondly according to the point cloud data features, we achieve a rapid, accurate and automatic method to determine secondary branches positions. Finally compared with manual tagged results, experiments prove the effectiveness of our method.

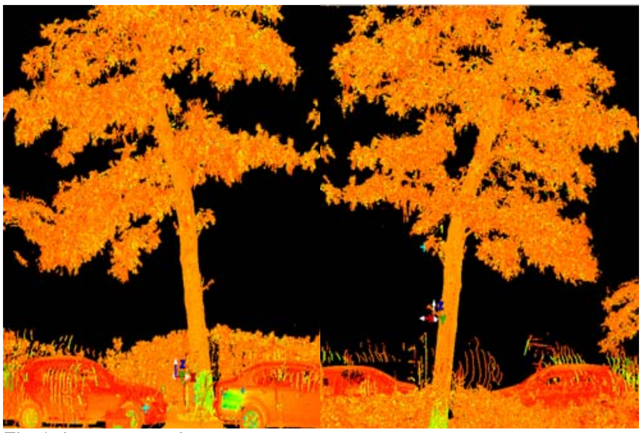


Fig.1. Laser scanning same tree

Point cloud data topological structure

Tree's model is belong to irregular complex objects, so tree's 3D model presents an extremely complex morphology, coupled with multi-angle acquisition data registration, the final scan stumpage point cloud have huge amount of data without any topological relationship, so how to quickly establish the point cloud topology structure becomes the foundation of forestry analysis.

Existing point cloud space partition method includes octrees, k-d tree and grid method. The former two methods need complicated pre-treatment process, for trees cloud point data with different morphology, algorithm will become more complex. In this paper, we use the uniform grid method combined with the sphere neighbourhood to calculate the point cloud topology structure. For space scattered point cloud data, we first calculate the maximum and minimum coordinates values of all data points, then according to these values create a rectangular box parallel to the coordinate, then the box is divided into a series of small cubes (called grids) with a given length, then all data points are classified into these corresponding grids by point coordinate values.

For a given point cloud data P, a single point $\{p_i, i = 1, 2, \dots n\}$ extrema on different coordinate axis are $x_{\max}$, $x_{\min}$, $y_{\max}$, $y_{\min}$, $z_{\max}$, $z_{\min}$. According to the given length L, cloud points space is divided into m grids, each grid point center is recorded as c'.

$$m = \left[\frac{(x_{\max} - x_{\min})}{L}\right]\left[\frac{(y_{\max} - y_{\min})}{L}\right]\left[\frac{(z_{\max} - z_{\min})}{L}\right] \quad (1)$$

Grid information is stored by the two-dimensional array, each point is stored into the index array corresponding to the grid. When we search the point neighbourhood, we first determine which grid g_p that current point p belongs to, then record all points p_g in the grid g_p and its adjacent grids, and calculate the points p_r in spherical space with center p and radius r, the intersection of p_g and p_r is neighbourhood points of p. As shown in formula 2:

$$\begin{aligned} &(p_x - c'_x) \le L \text{ and } (p_y - c'_y) \le L \text{ and } (p_z - c'_z) \le L \\ &\text{and} \quad \sqrt{(p_{nx} - p_x)^2 + (p_{ny} - p_y)^2 + (p_{nz} - p_z)^2} \le r \end{aligned} \quad (2)$$

Where (p_{nx}, p_{ny}, p_{nz}) represent current point neighbourhood coordinates.

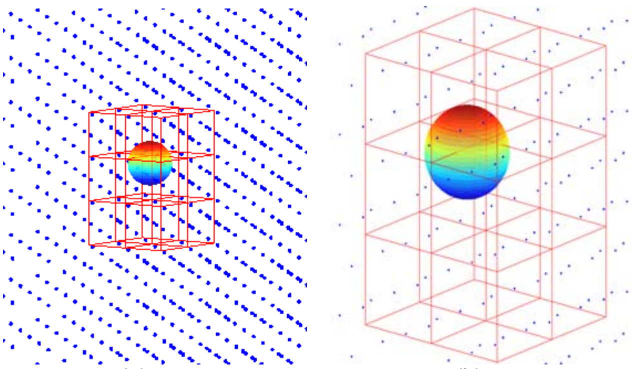

(a) (b)

Fig.2. cloud point neighbourhood calculation

Fig. 2(a) and (b) represent two point cloud grid map at different viewpoint and different distances, red lines show the grids, blue points represent each grid center, colour balls represent the neighbourhood sphere with center p and radius r, through the formula (2) calculation, we can access each point neighbourhood, thereby the point cloud calculation complexity is reduced.

Main stem extraction based on the Hough transform and continuous circle centers

Hough transform method is shown in literature [4], circle equation is:

$$(x-a)^2 + (y-b)^2 = r^2 \quad (3)$$

Where (a,b) represent circle centre and r represent circle radius. When the circle in the X-Y plane is converted to $a-b-r$ parameter space, any point (x,y) in $a-b-r$ space is corresponding to a cone, the cones are generated by all points (x_1,y_1) (x_2,y_2) (x_3,y_3) on one circle circumference will intersect at center point (a_0,b_0,c_0).Thus, the specific parameters of the circle can be obtained by detecting the intersection point. The conversion and calculation process are specifically shown in Fig. 3.

For the complex morphology of main stem, we used Hough transform detection method, after the main stem is segmented according to the height, segmental main stem are taken projection on the Z axis. $\bar{P} = F_z(P_i, i = 1,2,...n)$,

where F_z is projection function. By setting the circle radius and detection threshold, we take circle detection to the projection images, and then determine the main stem growth by corresponding circle factors, the specific test results are as follow:

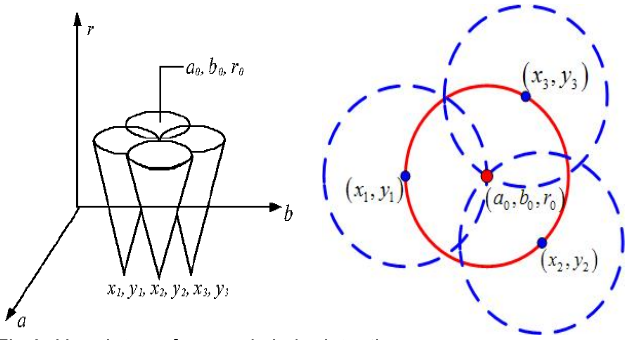


Fig.3. Hough transform and circle detection

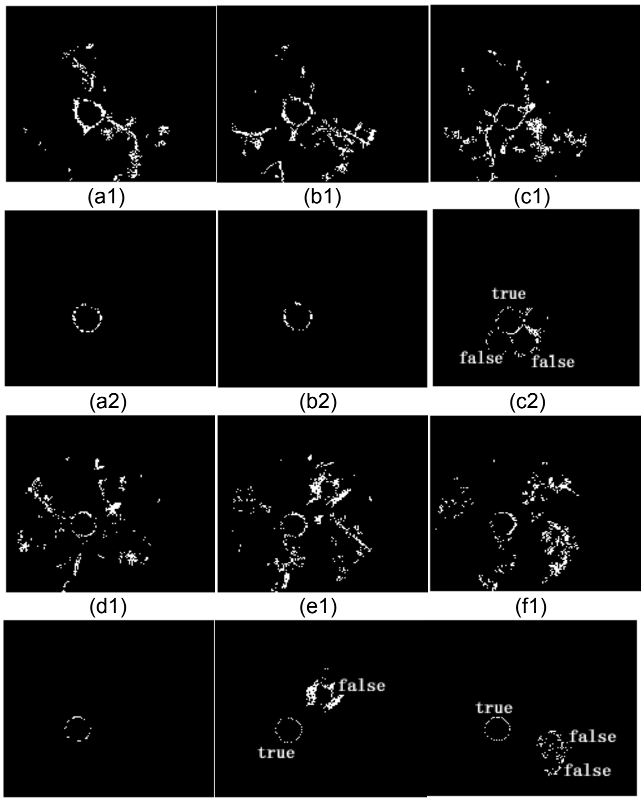
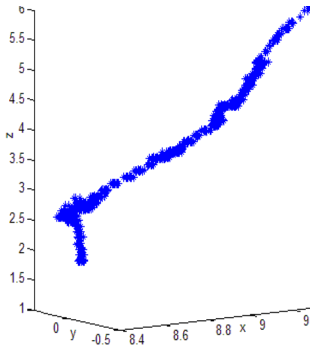


Fig.4. circle detection results of main stem sections

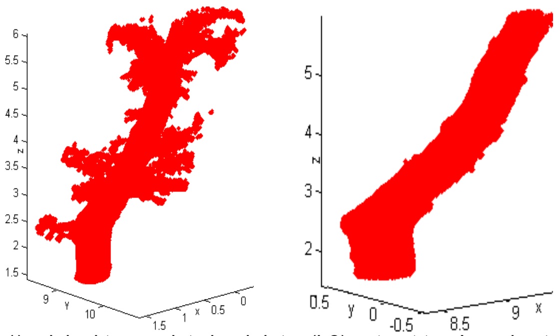
In Fig. 4.(a1,b1,c1,d1,e1,f1) are the main stem sections at different height, (a2,b2,c2,d2,e2,f2) are the corresponding results after Hough transform detection. As can be seen from the figure, sections (a1, b1, d1) are obtained right results; sections (c1, e1, f1) can't detect the right main stem location due to the influence of excessive foliage and branches. Seen from the test results (c2, e2, f2) can find the error detection circle. In order to avoid false circle detection, next we put forward main stem extraction method based on the continuous circle centers and Hough transform. As shown in formula (4):

$$\sqrt{(a_{z_1} - a_{z_2})^2 + (b_{z_1} - b_{z_2})^2} \le thresh_1, \quad z_2 = z_1 + 0.1 \quad (4)$$

where z_1 z_2 represent two contiguous different height, (a_{z_1}, b_{z_1}), (a_{z_2}, b_{z_2}) represent the main stem centers of the two contiguous different height, according to the centers continuity, the absolute distance between these centers should be less than a threshold, the distance between the error detection circles centers should be greater than the threshold, then locations of the main stem centers are determined. Using the formula (4) we obtain the skeleton of main stem, and combined the radius r to get the main stem three-dimensional model, just as shown in Fig. 5.



(a) Main stem skeleton consists by continuous circle centers



(b1) original tree point cloud data (b2) extract tree's main stem
Fig.5. main stem extraction based on the continuous centers

Trees point cloud data feature calculation

How to get stumpage forest parameters from these 3D point cloud data depend on the point cloud features calculation [5, 6]. Point cloud features including curvature, normal vector, and the angles between the normal, these important parameters represent the 3D point cloud changes. For the stumpage cloud points' 3D model, the extrema of these parameters correspond to the location of the branches and knot, these characteristics calculation method are given below.

For point cloud data P, suppose the neighbour points of a given point p_i is $p_{i1}, p_{i2} \ldots p_{ik}$, construct covariance matrix C_i constituted by $p_{i1}, p_{i2} \ldots p_{ik}$, then calculate the matrix minimum eigenvalue corresponding to the eigenvector, the eigenvector is the p_i normal vector, and according to the p_i local areas change to estimate the curvature

(5) $$C_i = \begin{bmatrix} p_{i1} - \bar{p}_i \\ \ldots \\ p_{ik} - \bar{p}_i \end{bmatrix}^T \begin{bmatrix} p_{i1} - \bar{p}_i \\ \ldots \\ p_{ik} - \bar{p}_i \end{bmatrix}$$

Where C_i is third–order positive semi-definite symmetrical matrix, $\bar{p}_i$ is p_i neighbour points center, calculate three eigenvalues $\lambda_1, \lambda_2, \lambda_3$ and the corresponding eigenvectors e_1, e_2, e_3 of the matrix C_i, eigenvalues arrange in ascending order, $\lambda_1 \le \lambda_2 \le \lambda_3$, λ_1 describe the variation of the surface along the normal direction, and the p_i normal vector is $n_i = e_1$, then curvature H_i estimation can be represented by the following formula:

(6) $$H_i = \frac{\lambda_1}{(\lambda_1 + \lambda_2 + \lambda_3)}$$

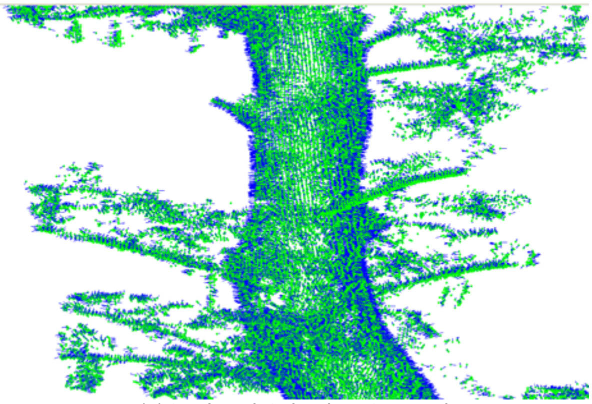
The change of the angle between normal vectors can measure surfaces curve or flat degree, the normal direction is applied to 3D point cloud model in this paper, in order to judge one point whether is a feature point, suppose p_i is any point in point cloud data G, p_j is the neighbour point of p_i, their normal vector is respectively n_{p_i} and n_{p_j}, the angle between the normal vector p_i and p_j can be expressed as: $\cos\theta_{p_i p_j} = \dfrac{n_{p_i} \bullet n_{p_j}}{|n_{p_i}| \times |n_{p_j}|}$, where the $\theta_{p_i p_j}$ value range is $[0, \pi]$. Taking summing operation of normal angles between one point with all of its neighbour points $M(p_i)$ will get the normal angle value: $w_a(p_i) = \sum_{p_j \in M(p_i)} \theta_{p_i p_j}$, normal angle value $w_a(p_i)$ shows the bending degree of the current data point p_i and its nearby neighbour points, if the $w_a(p_i)$ value increase, the bending degree of the surface is larger, the data points p_i neighbourhood is more likely feature area; Conversely, if the $w_a(p_i)$ value is less, the bending degree of the p_i neighbourhood is smaller and model surface is more smooth, thus it is remotely possible that p_i neighbourhood will be the feature area.

the data point p_i parameters include: mean $w_m(p_i)$, curvature H_i and normal angle value $w_a(p_i)$, then we define the data point p_i feature as: $w(p_i) = \dfrac{(\lambda_H H_i + w_a(p_i))}{\lambda_n w_m(p_i)}$. Where λ_H is curvature coefficient, λ_n is distance coefficient.

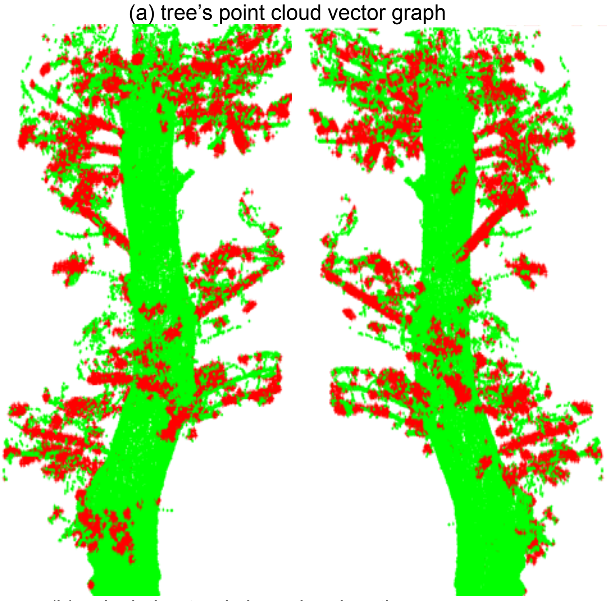
These parameters reflect the regional variation and flatness, point cloud at branches are usually with greater curvature variation and unfixed normal vectors, thus, the calculated features is correspond to the branches location. Specific experiments as shown in Fig.6, as can be seen from the Fig. 6(a), the normal vectors of main stem cloud points are consistent with same direction and size, but normal vector at branches are different from each other, Fig. 6(b) is the calculation result of $w(p_i)$, where the great value of $w(p_i)$ are corresponding to the red branches location.

Experimental results

The trees radius and branching positions are calculated by our method, and compared with manual extraction results from Lecia TLS data, the corresponding results as shown in Fig.7, test accuracy is 92.3 %.

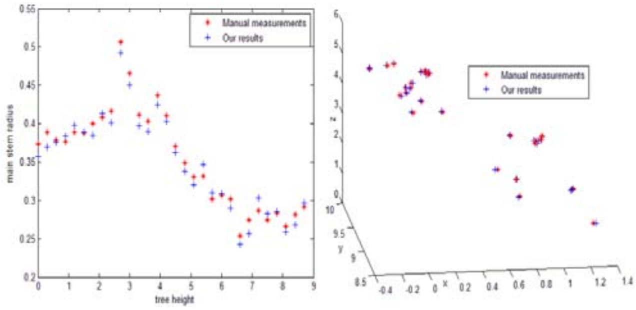


(a) tree's point cloud vector graph



(b) calculation tree's branches location
Fig.6. tree point cloud features detection

(a) Manually extract main stem diameter from lecia cyclone point data



(b) (c)
(b) Main stems radius results comparison
(c) Branches position results comparison
Fig.7. experimental comparison

Table 1. Results comparison

	main stem volume /(square meters)	detection branches number
Our method	1.148	28
Manual results	1.062	34

Conclusion

We research tree forestry parameters through the application of leica TLS, and combine with the computer graphics and iconography to automatically calculate tree volume and branches location, in comparison with manually obtain results, experimental analysis show that our method has a higher correct rate. In the future work we will do in-depth research on important forestry parameters such as leaf area index and canopy density.

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