Batch Extraction of Tree Stem From Natural Forest Based on Terrestrial Laser Scanning

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Research

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Abstract

Background: Aiming at the problems of low accuracy of tree stem extraction from point cloud data of natural forest and poor universality, a method for batch extraction of tree stem from natural forest point cloud data based on terrestrial laser scanning is proposed.

Methods: First, the principal component analysis method is used to calculate the point cloud eigenvalues and eigenvectors, and the information entropy is minimized as a constraint to achieve the best neighborhood scale selection; Then combined with the spatial distribution features of the three-dimensional forest, using the Z-axis component of normal vector as the feature variable, the threshold method is used to filter out a large number of non-stem point clouds, and the 3D features are used for rough extraction of tree stem point cloud; Finally, density clustering is used to realize the precise extraction of tree stem point cloud.

Results: Select the two typical representative natural forest sample plots of *Pinus densata* Mast. and *Picea asperata* Mast. in Shangri-La as the experimental data to extract stem. All the stem of the two natural forest sample plots were detected and extracted. Using the extracted individual tree stem point cloud and the true tree stem point cloud for correlation analysis, the $R^2$ of the *Pinus densata* Mast. sample plot was 0.990, and the $R^2$ of the *Picea asperata* Mast. sample plot with a more complex growth environment was 0.982.

Conclusions: The results show that this method can well achieve batch extraction of tree stem point cloud from natural forest, and has the characteristics of high extraction accuracy and strong adaptability.

Background

The stem of tree bears main function of nutrient transportation and is an important part of the forest (Leopold 1971). The growth morphology of tree stem is one of the important indicators for evaluating forests (Maltamo et al. 2006; Chiba 2000; Laasasenaho et al. 2005; Yu et al. 2013). Meanwhile, The measurement and statistics of tree parameters such as tree height and diameter at breast height (DBH) often start from the tree stem (Li et al. 2012; Liu et al. 2016; Liu et al. 2018), so the tree stem has important economic and Ecological value. The traditional forest tree stem survey method requires researchers to go deep into the forest area and use relevant instruments to perform measurement statistics (Meng 2006). Although this method can ensure the measurement accuracy, the main disadvantage of this method is time-consuming, laborious, and inefficient. The emergence and development of Light Detection And Ranging (LiDAR) remote sensing technology provides a new method for forest ecological investigation and research (Li et al. 2016; Pang et al. 2019; Liu et al. 2017; Yan et al. 2018). It can efficiently and accurately obtain the three-dimensional spatial structure of the forest, and further obtain forest information, which makes up for the shortcomings of traditional methods. Airborn Laser Scanning (ALS) and Terrestrial Laser Scanning (TLS) are the two main LiDAR technologies currently used in forest application research (Liu and Pang 2014). Because ALS technology is difficult to
obtain structural information below the forest canopy, it is mainly used in researches such as forest biomass and canopy parameter inversion (Li et al. 2015; Li et al. 2015; Xie et al. 2020). Compared with the ALS technology, the point cloud data obtained by the TLS technology can clearly and accurately characterize the three-dimensional spatial structure below the forest canopy, and has a great advantage in the research under the forest canopy. Therefore, the current research related to tree stem is mostly based on TLS technology (Tao et al. 2015; Ma et al. 2019; Wang 2019).

At present, many scholars have carried out many studies on the detection and extraction of tree stem using TLS technology. Common research methods can be roughly divided into two categories. One method is to perform cylindrical fitting for tree stem point cloud. For example, Olofsson et al. (2014) performed cylindrical fitting for tree stem point cloud based on RANSAC algorithm to obtain the trunk model. Duan and Liu (2020) processed point cloud data for filtering, smoothing and repair firstly, and then carried out modeling and extraction for tree stem point cloud based on PROSAC algorithm. Liang et al. (2012) used the local normal vector feature of the point cloud to extract the tree stem roughly, and then performed cylindrical fitting on the tree stem point cloud to obtain its growth model. The stem growth model constructed by this kind of method can directly represent the stem information, but its accuracy is easily affected by the growth environment, growth morphology and point cloud quality of the forest. Another method is to use the local neighborhood features of the point cloud to extract the tree stem point cloud. For example, Xia et al. (2015) extracted bamboo stem based on the linear features of the local neighborhood of the point cloud. Luo et al. (2019) extracted the stem based on the consistency of the main direction of the stem point cloud. Liang et al. (2014) extracted tree stem by comparing the discreteness of local point clouds, and believed that the smaller the discreteness of local point clouds, the greater the probability of the stem points. This kind of method can detect and extract forest tree stem point cloud to a certain extent, but it is still challenging to extract the high-precision point cloud of tree stem in natural forest using only a single point cloud feature. For example, the linear feature of the point cloud is not sensitive to the stem of trees with large DBH in natural forest.

In summary, in order to solve the problems of low accuracy and low universality of tree stem extraction, this paper proposes a method for batch extraction of tree stem from natural forest based on TLS point cloud data. The study uses the information entropy minimization as the constraint condition to adaptively obtain the best neighborhood radius to calculate the Z-axis component of the point cloud normal vector and the 3D features, combined with the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm to achieve High-precision extraction of point clouds of tree stem from natural forest.

Materials And Methods

Study area and data acquisition

Shangri-La City is located in the northwestern part of Yunnan Province, China (Fig. 1). It has rich vegetation types and extensive natural forest coverage (Yu et al. 2019; Chen et al. 2019). The main forest
types include *Pinus yunnanensis* Franch, *Pinus densata* Mast., and *Picea asperata* Mast. et al. Two typical and representative *Pinus densata* Mast. and *Picea asperata* Mast. forest sample plots were selected as experimental data in the study area. The center coordinates of the *Pinus densata* Mast. natural forest sample plot is N27°38', E99°45', and the elevation is 3269 m. There are few shrubs and weeds under the forest, and the trees grow sparsely. The center coordinates of the *Picea asperata* Mast. natural forest sample plot is N27°48′, E99°59′, and the elevation is 3697 m. The growth environment under the forest is complex, with bushes and weeds growing, and trees growing densely. The study uses Leica P40 3D laser scanner as the data acquisition device. The Leica P40 3D laser scanner is an excellent TLS point cloud data acquisition device that can efficiently and accurately acquire high-density point clouds. Its performance parameters are shown in Table 1. In order to obtain the point cloud data of the forest sample plot more completely, 3 inter-visibility targets were placed in the forest and scanned at 5 sites (1 center in the center and 4 nearby). After obtaining the cloud data of each site in the forest sample plot, the original point cloud data was obtained by stitching them according to the target position in the cyclone software, and finally the experimental data was obtained by denoising and cropping(Fig. 2).

![Table 1](image)

Leica P40 LiDAR specifications

| Indicator                  | Description                                                                 |
|----------------------------|-----------------------------------------------------------------------------|
| Range accuracy             | 1.2 mm + 10 ppm                                                             |
| 3D position accuracy       | 3 mm @ 50 m                                                                  |
|                            | 6 mm @ 100 m                                                                 |
| Wavelength                 | 1,550 nm (invisible); 658 nm (visible)                                      |
| Scan rate                  | Up to 1,000,000 points per second                                           |
| Field of view              | 360° (horizontal); 290° (vertical)                                          |
| Range and reflectivity     | Minimum range: 0.4 m                                                        |
|                            | Maximum range at reflectivity:                                              |
|                            | 120 m (8%), 180 m (18%), 270 m (34%)                                        |
| Range noise                | 0.4 mm RMS at 10 m                                                           |
|                            | 0.5 mm RMS at 50 m                                                           |

**Research process**

Different types of point clouds have different three-dimensional spatial geometric characteristics, and point cloud features have important applications in point cloud classification research (Yang and Dong 2013; Wang et al. 2019; Wang et al. 2019; Zhou et al. 2019; Zhao et al. 2020). There are two main characteristics of tree stem: (1) From an overall perspective, affected by the growth law of trees, the stem
are distributed vertically upwards and grow upwards basically perpendicular to the ground. (2) In a local area, it is generally cylindrical, while other non-stem point clouds have basically no three-dimensional features. According to the above-mentioned spatial distribution characteristics of tree stem, a tree stem extraction method based on TLS natural forest point cloud data is proposed, which is divided into two steps: rough extraction and precise extraction. The first step: Firstly, calculate the normal vector feature of the local neighborhood of the forest point cloud, and find its component $N_z$ on the Z axis. The smaller the $N_z$, the greater the probability that it is a tree stem point (Liang et al. 2012). Then, set a reasonable $N_z$ threshold to cycle and remove non-tree stem point clouds such as ground, shrubs and canopy to the greatest extent. Finally, according to the principle that the stem are distributed in a columnar shape in the local neighborhood, the forest tree stem are roughly extracted in combination with the 3D features. The second step: There are still some non-stem points around the rough tree stem point cloud extracted through the above steps. According to the feature that the tree stem point cloud is densely distributed in a certain xy plane, the distribution of non-tree stem points is relatively scattered. The DBSCAN algorithm is used to cluster the xy plane, and a small number of outliers are denoised and optimized to obtain a precise point cloud of the stem. The technical roadmap is shown in Fig. 3.

**Rough extraction of tree stem point cloud**

The point cloud normal vector feature and dimensional feature can be represented by the eigenvalues and eigenvectors of the covariance matrix of the point cloud within its local neighborhood radius $R$ (An et al. 2018). Calculate the eigenvalues ($\lambda_1, \lambda_2, \lambda_3, \lambda_1 > \lambda_2 > \lambda_3$) and eigenvectors ($n_1, n_2, n_3$) in the local neighborhood radius $R$ of the forest point cloud by using the Principal Component Analysis (PCA) algorithm (Hoppe et al. 1992). The eigenvector corresponding to the smallest eigenvalue is the normal vector. The calculation methods of the $N_z$ (Liang et al. 2012) value and dimensional feature line ($a_{1D}$), plane ($a_{2D}$) and volume ($a_{3D}$) (Ma et al., 2020) of the normal vector of the point cloud are shown in formulas (1) and (2).

$$N_z = |n_3 \times n_0|$$  

(1)

where, $n_0$ represents the vector [0,0,1].

$$a_{1D} = \frac{\sqrt{\lambda_1} - \sqrt{\lambda_2}}{\sqrt{\lambda_1}}, \quad a_{2D} = \frac{\sqrt{\lambda_2} - \sqrt{\lambda_3}}{\sqrt{\lambda_1}}, \quad a_{3D} = \frac{\sqrt{\lambda_3}}{\sqrt{\lambda_1}}$$  

(2)

The size of the local neighborhood radius $R$ of the point cloud has a greater impact on the features in the point cloud. The local features of a point cloud will change due to different neighborhood radius, so the use of a unified neighborhood radius will affect the extraction accuracy of the tree stem point cloud (Ma et al. 2019; Xuan et al. 2019). This paper takes the information entropy minimization as the constraint condition to adaptively obtain the best neighborhood radius $R$ to reduce the error (Demantké et al. 2011). The principle is shown in formula (3).
where, $E_p$ represents the information entropy of point $p$ in a certain neighborhood radius. The smaller the $E_p$ value, the more unitary the dimensional features of the point $p$ in the neighborhood, and the neighborhood radius is expressed as the best point $p$ radius. The steps for calculating the best neighborhood radius $R$ of point $p$ are: Firstly, determine a neighborhood radius interval $[R_{min}, R_{max}]$ and radius increment $\Delta R$. Then, loop to calculate the $E_p$ value of all radius of point $p$ in this radius interval. Finally, the $E_p$ value is compared, when the $E_p$ value is the smallest, the corresponding radius $R$ is the optimal radius.

Obtain the eigenvalue and eigenvalue vector corresponding to the best neighborhood radius $R$ of the point, and calculate the normal vector Z-axis component $N_Z$ to filter out most of the non-tree stem points such as the ground, shrub and canopy. Then use the three-dimensional spatial characteristics of the remaining point cloud to further roughly extract the tree stem point cloud.

**Precise extraction of tree stem point cloud**

The DBSCAN algorithm is an algorithm based on density clustering. It does not need to know the number of clusters, can find clusters of any shape, and can also identify noise points (Ester et al. 1996). Suppose that the points $p$, $q$, and $c$ are three points in the point cloud set $D$. In the DBSCAN algorithm, several important definitions are as follows. (1) Parameters $Eps$ and $MinPts$: They respectively represent the radius of the spherical neighborhood of a point and the minimum number of points forming a cluster. These two parameters need to be defined in advance. (2) Core points, edge points and outlier points: If the number of points in the $Eps$ neighborhood of point $p$ is greater than $MinPts$, then point $p$ is called the core point. If the number of points in the $Eps$ neighborhood of point $q$ is less than $MinPts$, but point $q$ is in the $Eps$ neighborhood of point $p$ or other core points, the point $q$ is called the boundary point. The point that does not meet the above two conditions is called the noise point. (3) Directly density-reachable, density-reachable and density-connected (Guo et al. 2018): if point $p$ is the core point, and point $q$ is in the $Eps$ neighborhood of point $p$, then point $q$ is called the directly density-reachable of point $p$. If the point $q$ is directly density-reachable of point $p$, and the point $c$ is directly density-reachable of point $q$, then point $c$ is called the density-reachable of point $p$. But the density-reachable is only between the core points. If point $p$ and point $q$ are all density-reachable of point $c$, then point $p$ and point $q$ are called density-connected. The principle of clustering in the DBSCAN algorithm is to find the density-connected maximum point set in the point cloud set $D$ to form a cluster, which achieve the purpose of clustering.

According to the principle of the DBSCAN algorithm, the tree stem are clustered and then extracted, and a small number of outliers are denoised and optimized to realize the precise extraction of the tree stem point cloud.

**Results**
Matlab R2019b was used as the experimental platform to process the cloud of the *Pinus densata Mast.* sample plot that total number of point is 1972282. Set the neighborhood radius interval to [0.1, 1], the increment $\Delta R$ is 0.2, calculate the best neighborhood radius of the point, and get the eigenvalue and eigenvector corresponding to the best neighborhood radius.

The first step is to roughly extract the stem points. Firstly, calculate the $N_Z$ value with the normal vector. Then set a reasonable $N_Z$ threshold $T$, and extract points with $N_Z < T$ to reduce the influence of non-stem points on the extraction of tree stem. When the threshold $T$ is 0.1 and 0.2, the results of removing ground, shrub and canopy points are shown in Fig. 4. It can be seen from Fig. 4 that when $T$ is 0.1 and 0.2, the stem point will be missing (the red part in the Fig. 4) for the sloping and curved stem.

When the threshold $T$ is 0.3 and 0.4, the results of removing ground, shrub and canopy points are shown in Fig. 5. It can be seen from Fig. 5 that the stem points of the sloping and curved tree can be preserved. However, when $T$ is 0.3, the stem point cloud can be completely retained, while the ground point cloud, shrub point cloud and canopy point cloud can be filtered out to the maximum. Therefore, we loop this step with the extraction result of $T$ is 0.3, filter out most of the non-stem point clouds, and minimize the influence of other types of point clouds on the extraction of tree stem point clouds. After 5 looped, we found that the non-stem points have been removed to the maximum extent, and the result is shown in Fig. 6.

Finally, 3D features are used for the remaining points to further remove the non-stem point cloud, and obtain the rough extraction result of the stem. In order to determine the size of the 3D features value of the point cloud of the tree stem, the tree stem within the height range of 3 m – 6 m from the experimental data are sampled and the 3D features value of each point is counted. Figure 7(a) shows the numerical distribution of the tree stem point cloud in the 3D features, indicating that the point with the 3D features value roughly within [0.05–0.5] is the tree stem point. Extract the points whose 3D features values of the remaining points in the previous step are within [0.05–0.5], and get the rough extraction result of the tree stem point cloud, as shown in Fig. 7(b).

The second step is the precise extraction of the tree stem point cloud. The DBSCAN algorithm is more sensitive to two input parameters Eps and MinPts. When Eps is larger and MinPts is smaller, the number of clusters will decrease, causing other types of point clouds to be classified as tree stem point clouds. When Eps is smaller and MinPts is larger, the number of clusters will increase, resulting in tree stem point clouds being classified as other types of point clouds. After research and comparison, for the experimental point cloud of the *Pinus densata Mast.* sample plot, it is found that when Eps is in the interval of [0.02, 0.04] and MinPts is in the interval of [20, 30], the tree stem point cloud extraction can obtain higher accuracy results. Figure 8 shows the precise extraction results of the stem when Eps is 0.03, MinPts is 25, and a small amount of outlier noise points are removed.

In terms of the number of stem identified, the method in this paper can detect and extract all the stem in the *Pinus densata Mast.* sample plot with a precision of 100%. In order to verify the accuracy of the
extraction of each single tree stem, the tree stem of the original experimental data were manually extracted. Correlation analysis was performed between the stem extracted manually and the stem points extracted by the method in this paper, and $R^2$ was 0.990, as shown in Fig. 9. It shows that the tree stem points extracted by this method have high accuracy.

The experiment was conducted on *Picea asperata* Mast. sample plot with a more complex growth environment and densely growing trees. The number of points was 2725298. The results of the stem are shown in Fig. 10. The stem of the *Picea asperata* Mast. sample plot were manually extracted and the accuracy was analyzed. The results show that the method in this paper can still detect all the stem in the sample plot, and the extraction accuracy of the number of stem is 100%. The same correlation analysis was performed between the stem extracted manually and the stem points extracted by the method in this paper, and $R^2$ was 0.982, as shown in Fig. 11. The results show that in natural forests with complex growth environment, this method can still obtain high-precision stem extraction results.

**Discussion**

At the end, we analyzed the factors that affect the accuracy of stem extraction, and compared the stem extraction results of the two sample plots, as shown in Fig. 12. From the extraction results of the stem of the two sample plots, it can be seen that the stem below the canopy can be extracted with high precision, and the stem with branches can also be extracted (*Pinus densata* Mast. (e) in Fig. 12), the error mainly comes from the upper part of the canopy. We found that there are two main factors affecting the extraction of stem from the upper part of the canopy. (1) Differences in tree species growth. Compared with the *Picea asperata* Mast. sample plot, the upper part of the stem of the *Pinus densata* Mast. sample plot is not cleanly extracted, and there are some secondary branch point clouds. This is mainly related to the difference in the growth morphology of the two tree species. There are many secondary branches growing in the *Pinus densata* Mast. canopy, and the growth is relatively dense. Therefore, during the extraction of the stem, there are still many secondary branch point clouds on the upper part of the stem of the *Pinus densata* Mast. sample plot that are not easy to remove, which affects the extraction accuracy. (2) Canopy occlusion. From the extraction results of the two plots, the tree stem in the upper part of the canopy have missing point clouds. This is mainly because when data is collected, due to the growth of natural forest trees, the upper part of the canopy is severely occlusion from each other, and it is difficult to obtain a complete point cloud of the upper part of the canopy. Therefore, as the height of the tree increases, the stem extraction accuracy is also decreasing.

**Conclusions**

In order to solve the problems of low accuracy of tree stem extraction from natural forest and poor universality, the research proposed a method for batch extraction of tree stem based on TLS point cloud data of natural forest. The Z-axis component of the normal vector and the 3D features of the point cloud are calculated through the adaptive neighborhood radius, and finally the DBSCAN algorithm is used to extract the stem of the natural forest. All the stem of the two natural forest sample plots were detected
and extracted. Through correlation analysis with the manually extracted stem points, it was found that the stem extraction $R^2$ of the *Pinus densata* Mast. sample plot was 0.990, indicating that the extraction accuracy was high. High-precision stem extraction results were still obtained in *Picea asperata* Mast. sample plot with complex growth environment. Stem extraction $R^2$ of *Picea asperata* Mast. sample plot was 0.982. However, it is also found that the two factors of tree species growth difference and canopy occlusion have a greater impact on the extraction accuracy of the upper part of the stem. How to reduce the influence of these two factors on the extraction of the stem and further improve the extraction accuracy will be the future research focus.

**Abbreviations**

DBH: Diameter at breast height; LiDAR: Light Detection And Ranging; ALS: Airborn laser scanning; TLS: Terrestrial laser scanning; DBSCAN: Density-based spatial clustering of applications with noise

**Declarations**

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Not applicable.

**Author contributions**

Jinliang Wang, Weifeng Ma and Jianpeng Zhang conceived and designed the experiments; Jianpeng Zhang and Qianwei Liu performed the experiments; Yicheng Liu and Zhiyan Zhang analyzed the data; and Jianpeng Zhang wrote the paper. All authors read and approved the final manuscript.

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**Availability of data and materials**

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

**Ethics approval and consent to participate**
The subject has no ethic risk.

**Consent for publication**

Not applicable.

**Competing interests**

The authors declare that they have no competing interests

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