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Using point cloud data for tree organ classification and real leaf surface construction

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Terrestrial Laser Scanning (TLS) enables easy and fast Point Cloud Data (PCD) acquisition from objects, and it has been widely used in complex scene survey. However, trees have seriously irregular and complex morphology, and scanning process always be influenced by external environment variation and have occlusion effect, so quantifying the 3-D morphology structure and assessing parameters of forest stands by TLS is challenging. In order to solve these problems, we applied computer technique to improve Terrestrial Laser Scanning (TLS) performance in forestry measurement. Here, new PCD feature vectors, including shape, orientation, normal vector distribution and normal vectors of tangent plane, was proposed, and Supervised Locally Linear Embedding (SLLE) algorithm and Gaussian Mixture Model (GMM) were adopted for the feature dimensionality reduction and PCD classification as well. Hence, the algorithm efficiency was improved and various tree organs could be automatically identified. Moreover, a leaf modeling method using polynomial fitting method and Moving Least Squares (MLS) were presented to depict real foliage silhouette and eliminate ghost points, yielding accurate reconstruction of complex foliage surface. As detailed experimental comparison stated, the recognition rate remained higher than 87.51 % while our classification method was applied to different tree PCD, and accurate 3D morphological reconstruction of leaf models have similar leaf area versus manually LI-3000C measurement results. Thus, our method show promise in further exploration of utilizing TLS as an effective tool for forestry parameter retrieval.

Keywords*:* Terrestrial Laser Scanning (TLS), Point Cloud Data (PCD), Tree organ classification, Leaf surface reconstruction.

INTRODUCTION

The forest has an irreplaceable status and role in regulating the earth's environment for human survival and slowing down and even curbing the global environmental degradation trend. Moreover, forest measurement science and forestry information research have become an important issue in recent years, we have to face the task that exploring the fine measurement of forest trees and providing an effective way to improve the accuracy and efficiency of forestry data collection for forestry surveying.

In recent years, quite a few methods of analyzing plant structure and measuring plant parameters was proposed, which could be divided into two types.

Firstly, tree measurement method based on the image processing and computer graphics theory is designed to calculate ecological parameters of the plants. Image recognition methods [1,2] was adopted to analyse numerous leaf images in order to classify different plant species. 3D reconstruction model of plant was utilized to characterize tree structures, light interception within the canopy and leaf photosynthetic capacity [3,4,5]. Moreover, a multitude of computer software, including YPLANT [6], Arbaro [7], VegeSTAR [8] and Speedtree [9] were designed for bio-simulation.

Secondly, laser scanning shows incomparable advantages in tree measurement in recent years. Many researchers selected Terrestrial laser scanner to obtain spatial explicit points representing target trees, and proposed a plethora of methods on basis of scanning data to retrieve ecological parameters. These achievements include developing PCD feature histograms to reflect plant geometrical information [10], reflecting changes in the deep oxidation state of the xanthophylls cycle from TLS return intensity [11], presenting voxel-based method with line quadrat direction to retrieve the biophysical characteristics of the forest canopy [12,13] and modeling laser-vegetation interactions probabilistically based on Poisson gap model [14], and so on. Besides, airborne laser scanning (ALS) offers an opportunity to conduct large scale surveying of vegetation at great resolution than has

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previously been available. Commercially-available equipments, such as aircraft and drones, loaded laser scanners and was manipulated by engineers to rapidly generate point-cloud data of vegetation. Corresponding algorithm were proposed for a broad range of forestry and environment management applications, such as forest biomass estimation [15], delineation of individual tree crown [16], aboveground biomass and carbon storage evaluation [17,18] and tree species recognition [19].

Although a number of researches have done considerable work on agricultural and forestry measurement, three challenging questions still remained in forestry parameters acquisition from scanning data. 1) How do we extract and distinguish every leaf from the flourishing tree's PCD with enormous variation in leaf inclination angle and azimuth angle? 2) The scanning data exists noise and deviation caused by occlusion effect and external environment interferences [20]. How do we eliminate deviation and design appropriate algorithm to construct real foliage data? 3) The presentation of scanned leaf is in the discrete points and not 3D surface model. How do we design a reasonable algorithm realizing the transformation from scanned point to leaflet surface.

Based on the above issues, here, two meaningful works have been done on basis of PCD. Firstly, original feature vector composed by normal vector, normal vector distribution and normal vectors of tangent plane was proposed, and supervised manifold learning method was designed to process these feature vectors for principal component analysis and dimensionality reduction. Then, Gaussian Mixture Model (GMM) and Expectation-Maximization (EM) method were adopted to the processed features in order to realize PCD classification and automatically recognize tree organs. Secondly, we established polynomial equations to fit leaf boundaries based on PCD, and manipulated MLS algorithm to eliminate noise points caused by external interference. Then, Delaunay triangulation method was introduced to generate numerous triangle meshes composing real leaf surface.

MATERIALS AND METHODS

Data collection by TLS

Our experimental trees were chose on the campus of Nanjing Forestry University $\left(32^\circ\,08'N, 118^\circ\,81'E\right)$, including many well-isolated individual trees such as Michelia trees and Sakura trees. Assuming that the shape of target tree crowns is ellipsoidal, each scan was obtained in azimuthally symmetric location and target tree located in the centre of the experimental plot. Every TLS placed in turn at different lateral side and kept several meters away from target tree. After TLS scanning procedure finished, every scan of different angle was finally integrated into a single coordinate system through registration process to acquire full coverage of objective trees.

Extraction of PCD feature

The features we employed include color, shape and orientation information. For every point $p_i = \left(x_i, y_i, z_i\right)$ in point cloud P, $P \subset R^3$, its surrounding finite space is defined the set of k nearest points $p_j = \left(x_j, y_j, z_j\right)$ with the mean being $\overline{p}_j = \left(1/k\right)\sum_{j=1}^{k} p_j$, The covariance matrix C_P of point p_i is defined by $C_{p_i} = \frac{1}{k}\sum_{j=1}^{k}\left(p_j - \overline{p}_j\right)^T\left(p_j - \overline{p}_j\right)$. Let $e_i = \left\{e_i^0, e_i^1, e_i^2\right\}$ be the eigenvector and $\lambda_i = \left\{\lambda_i^0, \lambda_i^1, \lambda_i^2\right\}$ be the corresponding eigenvalue of C_{p_i} and $\lambda_i^0 \le \lambda_i^1 \le \lambda_i^2$. e_i^0 corresponding to the minimum λ_i^0 approximates the normal vector at point p_i.

Next, we computed the covariance matrix of normal vector about this neighborhood using equation (1), where $\overline{e}_i$ denotes the mean normal vector of the 3D points in the neighborhood $\overline{e}_i = \left(1/k\right)\sum_{j=1}^{k} e_j^0$.

$$V_p = \frac{1}{k}\sum_{j=1}^{k}\left(e_j^0 - \overline{e}_i\right)\left(e_j^0 - \overline{e}_i\right)^T \qquad (1)$$

Consequently, Eigenvalue Decomposition on this covariance matrix V_p was performed to get three eigenvalues $l_i^0\ l_i^1\ l_i^2$ of V_p. For isotropic spatial distributions (corresponding to fruits), always $l_i^0 \approx l_i^1 \approx l_i^2$; for predominantly linear distributions (branches), $l_i^0 \ge l_i^1 \approx l_i^2$; and for roughly planar distributions (leaves), $l_i^0 \approx l_i^1 \ge l_i^2$.

Next, we calculated local tangent space feature of every point cloud. Assuming that the set of data points are sampled from a d-dimensional affine subspace, i.e.,

$$p_j = c_i + Q_i\theta_j + \varepsilon_j \quad \left(1 \le j \le k\right) \qquad (2)$$

where $\varepsilon_j \in R^3$ represents noise vector, $\theta_j \in R^d$ is projection coordinates about p_j on the local tangent space, $\Theta_i = \left[\theta_1, \theta_2, ..., \theta_k\right]$ and $d \le 3$. $c_i \in R^3$

is the origin coordinates of the tangent space and $Q_i \in R^{3\times d}$ is a matrix which forms an orthonormal basis of the affine subspace. The problem of linear manifold learning amounts to seek c_i, Q_i, θ_j to minimize the reconstruction error, i.e.,

$$\min_{c_i,Q_i,\theta_j} \sum_{j=1}^{k} \left\| p_j - c_i - Q_i\theta_j \right\|_2^2 = \min_{c_i,Q_i,\theta_j} \left\| p_j - c_i - Q_i\Theta \right\|_2^2 \qquad (3)$$

The matrix of p_i neighborhood is also denoted as $X_i = [p_1, p_2, ...p_k]$, and we extract local information by calculating the eigenvectors and eigenvalue of the correlation matrix $\left(X_i - \overline{p}_i\iota^T\right)^T\left(X_i - \overline{p}_i\iota^T\right)$, where $\overline{p}_i = \frac{1}{k}\sum_{j=1}^{k} p_j$, ι is a k-dimensional column vector of all ones. i.e.,

$$X_i\left(I - \frac{1}{k}\iota\iota^T\right)X_i^T = U_i\Lambda_i U_i^T \qquad (4)$$

where $U_i = \left[u_i^1, u_i^2, ...u_i^k\right]$ is orthogonal matrix, and the diagonal elements of the diagonal matrix Λ_i are monotone decreasing, so the local tangent space information for the sample point p_i is calculated:

$$\begin{cases} c_i = \frac{1}{k}X_i\iota \\ Q_i = \left[u_i^1, u_i^2, ...u_i^d\right] \\ \Theta_i = Q_i^T X_i\left(I - \frac{1}{k}\iota\iota^T\right) \end{cases} \qquad (5)$$

From the above derivation, we can calculate the column vector u_i^m which is corresponding to the smallest diagonal element of Λ_i, and u_i^m is also the normal vectors of local tangent space on p_i.

We represented the features of a given point p_i using the color information (r_i, g_i, b_i), normal vector e_i^0, normal vector distribution $l_i^0\ l_i^1\ l_i^2$ and normal vectors of tangent plane u_i^m to form 12-dimensional feature vector $c_{pi} = \left\{r_i, g_i, b_i, e_i^0, l_i^0\ l_i^1\ l_i^2, u_i^m\right\}$ for each point in the cloud. Consequently, these features were taken into the supervised manifold learning method to extract the principal component for realizing dimensionality compression.

Feature optimization by supervised LLE

Sam [21] proposed nonlinear dimensionality reduction algorithm by Locally Linear Embedding (LLE), which include unsupervised LLE and supervised LLE algorithms. Here, supervised LLE was introduced to deal with PCD features for improving algorithm efficiency.

Specific steps of the SLLE are as follows: Firstly, we separated whole PCD into training samples and testing samples, The features of training samples denote as $C_{q\times H}$. Through the LLE projection we can get $Y_{t\times H}$, where q is original dimension of training samples, t is output dimension of training samples, H is the numbers of training samples; Let C' be the set of testing samples, and choose one test sample c_{H+1}, $c_{H+1} \in C'$. c_{H+1} is taken into the matrix $C_{q\times H}$, then the matrix size of $C_{q\times H}$ becomes $q\times(H+1)$. Afterwards, try to finding K nearest neighbors of c_{H+1} in testing samples. The Dijkstra distance is used as a similarity measure, but for the testing samples, the priori category information cannot be taken into account. Secondly, find weight coefficients of c_{H+1} and its k-nearest neighbor points, which satisfy the following conditions: $\min \varepsilon_{\Pi}(W) = \left| c_{H+1} - \sum_{j=1}^{k} w_j^{H+1} c_{H+1,j} \right|^2$, where $\sum_{j=1}^{k} w_j^{H+1} = 1$. $c_{H+1,j}$ $(j = 1, 2, ..., k)$ are the neighbor points of the c_{H+1}, w_j^{H+1} is the weight coefficients between c_{H+1} and $c_{H+1,j}$. Thirdly, the LLE algorithm is used to find low-dimensional embedding features of the testing samples, which preserve the geometries inalterability in a low-dimensional space. Through the SLLE transform, training samples and testing samples of PCD are projected into the low dimensional space with the invariance of main characteristics, the original features c_{pi} of point p_i reduce to low-dimensional vectors $\Im_{pi}$.

PCD classification based on GMM

Our tree PCD data set was manually labeled as two semantic classes (branch and leaf). Using a portion of the data, Gaussian Mixture Model (GMM) classifier was used to classify tree PCD.

A Gaussian mixture model is a weighted sum of A component Gaussian densities as given by following equation.

$$p\left(\Im_p \middle| \lambda\right) = \sum_{i=1}^{A} \omega_i g\left(\Im_p \middle| \mu_i, \sigma_i\right) \qquad (6)$$

where $\Im_p$ is processed PCD features. $g\left(\Im_p \middle| \mu_i, \sigma_i\right)$, $i = 1, ..., A$, are the component Gaussian densities. Each component density is a Gaussian function of the form, with mean vector μ_i and covariance matrix σ_i, and ω_i is the weight coefficient of each class. The expansion formula of g is:

$$g\left(\Im_p \middle| \mu_i, \sigma_i\right) = \frac{1}{\left(2\pi\sigma_i\right)^{1/2}} \exp\left\{-\frac{1}{2}\left(\Im_p - \mu_i\right)' \sigma_i^{-1}\left(\Im_p - \mu_i\right)\right\} \qquad (7)$$

The mixture weights satisfy the constraint that $\sum_{i=1}^{M}\omega_i = 1$. The mean vectors, covariance matrices and mixture weights from all component densities parameterize GMM. These parameters are collectively represented by the notation, $\lambda = \{\omega_i, \mu_i, \sigma_i\}$, $i = 1,..., A$. Then the Expectation Maximization (EM) algorithm is proposed to maximize the likelihood $p(\Im_p|\lambda)$ of the data $\Im_p$ drawn from an unknown distribution. Specific formula is expressed as follows:

$$\lambda^* = \arg\max_{\lambda} \prod_{j=1}^{n} \sum_{k=1}^{A} \omega_k g(\Im_{pj}, \lambda_k) \tag{8}$$

where n represents the number of whole PCD. The output of the SLLE, GMM and EM generated an integrated classification for scanning points based solely upon their feature vectors.

Foliage surface reconstruction

TLS scanned data always be interfered by plant swaying in the wind and perspective occlusion. This section addressed accurate leaf boundary detection and 3D leaf surface reconstruction on basis of discrete points.

Foliage boundary depiction

TLS rangefinder system was based upon the principle of time-of-flight measurement of short infrared laser pulses. A rotating polygon mirror wheel realizes the line scan measurement and the frame scanner mechanism relies on rotating the optical head together with the fast line scan mechanism. Both the vertical scan and tilt scan covering the whole field of tree can produce global scan with a line scan angle. Thus, the tree PCD obtained by TLS show linear characteristics and can be represented by linear function $y_i = k_i x_i + b_i$ on horizontal (X-Y) plane. After each scan line equation was obtained, we can easily determine the endpoints of every scanning line, which represent the edge points of scanned foliage. These edge points at left and right sides can be denoted as $P_{Ledge} = \{(x_{l1}, y_{l1}, z_{l1}), (x_{l2}, y_{l2}, z_{l2}), ...(x_{ln}, y_{ln}, z_{ln})\}$, $P_{Redge} = \{(x_{r1}, y_{r1}, z_{r1}), (x_{r2}, y_{r2}, z_{r2}), ...(x_{rn}, y_{rn}, z_{rn})\}$, respectively. Under the guidance of polynomial fitting, we firstly proposed fitting algorithm to locate the true leaf boundary points based on each half-side edge points. To the end points $P_{Ledge} = \{x_l, y_l, z_l\}$, the magnitudes of y_l was taken as input parameters to calculate the corresponding fitting x_l' and z_l' values. Polynomial fitting was adopted to find the polynomial coefficients $v^x(x_l, y_l)$ with term number n' that make the data x_l' close to x_l , i.e., $x_l' \approx x_l = v_1^x y_l^{n'} + v_2^x y_l^{n'-1} + v_3^x y_l^{n'-2} + ... + v_{n'-1}^x y_l + v_{n'}^x$, where x_l' is calculated value to substitute x_l . Likewise, Polynomial fitting was also used to obtain fitted z_l' substituting initial z_l. The specific formula is as follows: $z_l \approx z_l' = v_z(y_l) = v_1^z y_l^n + v_2^z y_l^{n-1} + v_3^z y_l^{n-2} + ... + v_{n'-1}^z y_l + v_{n'}^z$. Thus, smooth outer contour of each foliage could be delineated when the fitted boundary points $P'_{edge} = \{x_l', y_l, z_l'; x_r', y_r, z_r'\}$ are connected in sequence.

Leaf surface fitting based on MLS

In this step, we smoothed and re-sampled data for each leaf point cloud using the Moving Least Square (MLS) method [22]. The algorithm fitted a 2D manifold to the 3D point cloud data and re-sampled the points to place them on the estimated surface. The method also provided surface normal and curvature estimates and up-sampled or down-sampled the point set appropriately. After MLS fitting processing, foliage scanned point $p_i = (x_i, y_i, z_i)$ was transformed into $p_i' = (x_i, y_i, z_i')$.

Delaunay triangulation was applied to convert every point p_i' into smooth leaf surface as triangular mesh.

As shown above, we extended method to deal with foliage silhouette delineation and smooth surface reconstruction on basis of PCD. Our method is intuitive and well suited for processing deviations caused by leaf jitter in wind and perspective occlusion. Visually important aspects of foliage appearance such as posture and smooth boundary be easily captured and described. Next, the experiments were conducted to demonstrate the effectiveness of our approach.

RESULTS AND DISCUSSION

Every target trees including Michelia tree and Sakura tree on our campus was scanned from three side-lateral locations with a middle sampling resolution and three markers were used as reference to align the three scans. Then, the ground points were removed and each individual tree was isolated for analysis.

Plant organs classification

After applying our algorithm to TLS point cloud data of an individual tree, we obtained a promising classification result as shown in Fig 1.

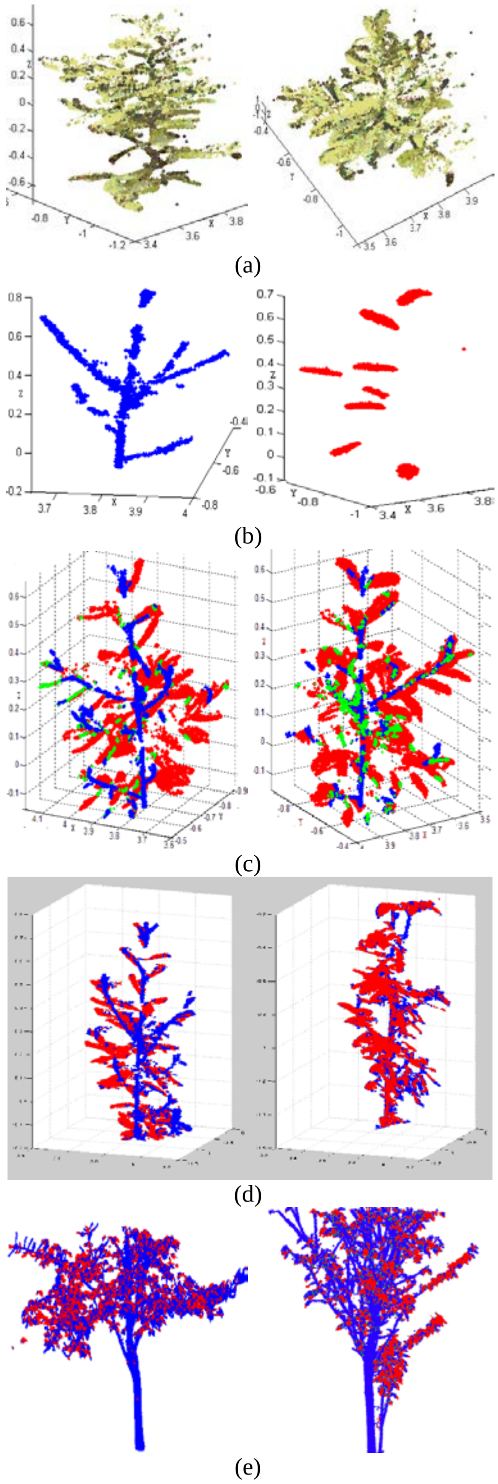

Fig. 1. Visualization of final classification of different components being to an individual tree. (a) Original point cloud data of Michelia tree. (b) Partially selected PCD was manually labeled as two classes (branch and leaf), which was taken as training samples of SLLE and used in GMM. (c) Preliminary classification with linear class points in blue color (i.e., branches and stems), surface class points in red color (i.e., leaves and shoots) and undetermined class points in green color. (d) Adjusted classification of Michelia tree after adapting algorithm parameters. (e) Final classification of Sakura tree after correcting misclassified points by our method.

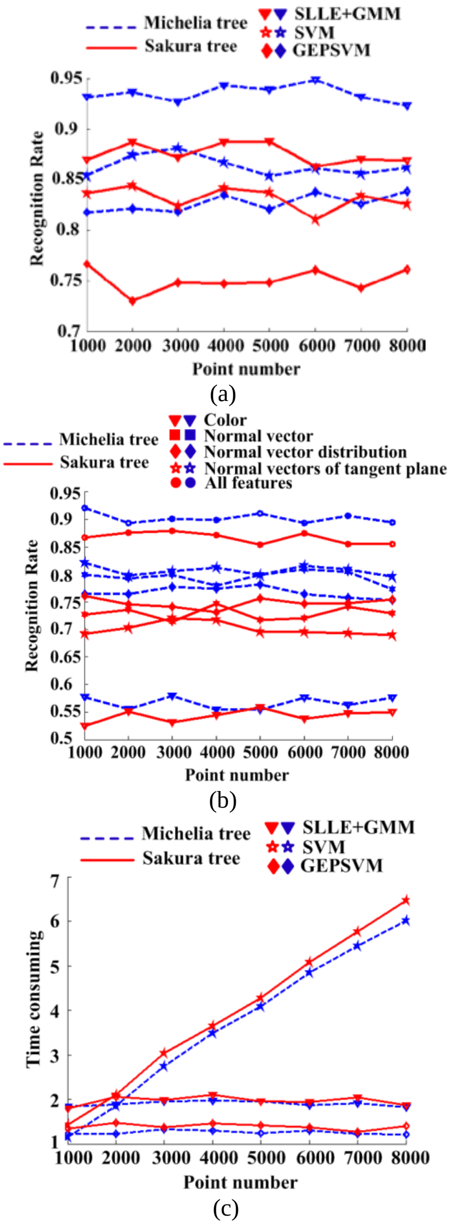

Fig. 2. Comparison with various algorithms and feature sets. (a) Recognition rates of different classifiers. (b) Recognition results using different feature sets. (c) Computation time of different classifiers.

The misclassification of minor points was occurred while leaves and shoots were misclassified as linear class due to perspective occlusion. Besides, small branches shaded by surrounding leaves always be misclassified as planar class. However, for most of scanned data, our method can identified photosynthetic and non-photosynthetic components using color, orientation and geomantic information. These salient features make the proposed method robust to lighting and inevitable color changes as the plant matures. Thus, obtaining better non-destructive measurements of foliage from tree PCD are realized for convenient leaf area estimate.

Consequently, we conducted a comparison with different classifiers and feature sets. Fig. 2 (a) shows that our SLLE + GMM classification method achieved a significant improvement in tree organ recognition. There are 92.38 % and 87.51 % recognition rate on the Michella tree and Sakura tree, respectively. The result is higher than other similar algorithms such as SVM and GEPSVM[23], which is shown in Fig. 2(a). Color, normal vector, normal distribution and normal vectors of local tangent plane of PCD features were respectively adopted to address the recognition rate of our method. It is clearly visible from Fig. 2(b) that all feature combination gives the highest recognition rate, with an average recognition rate of higher than 85.01 %. Due to the interference of external environment light, the minimal average recognition rates depending upon the color features only achieve average 50.27 %. In terms of time consuming, our algorithm takes similar time with GEPSVM method, but less time than other semi-supervised SVM classification methods, which is shown in Fig. 2 (c).

Plant leaf reconstruction

In order to test validation of our leaf surface construction algorithm, we preliminarily measure real Michelia leaf by LI-3000C portable area meter, which can displays and stores plant parameters such as: individual leaf area, accumulated area, leaf length and width. The practical experiment conducted by our student was shown in Fig 3(a).

Consequently, 3D watershed algorithm was designed to separate each leaf from whole leaf PCD and the classification results were shown in Fig 3(b).

We randomly chose some classified foliage data for 3D reconstruction, and Fig. 4 illustrates tree leaves modeling process on basis of PCD. Fig 4(a) shows classified scanned points of one leaf, where the green points are the original scanning PCD with noise and deviation and show linear arrangement along laser beam emitting angle. The linear equation was adopted to fit each scan line that likes blue lines in Fig 4(a). Preliminary leaf silhouette was labeled by the endpoints of each line. Then, we focused on the half side endpoints of every blue line and adopted polynomial curve fitting method to draw two fitting surfaces, and the x_l and z_l magnitude of these points were modified to define smooth and real leaf boundary through the intersection algorithm of these two surfaces. The process was shown in Fig 4(b). After the detection of leaf boundary, we discarded outlier points outside the leaf silhouette, and then the Least Squares (LS) estimation and Moving Least Squares (MLS) method were adopted to the residual foliage points for eliminating deviation caused by wind. Fig. 3(c) is the result of foliage surface fitting through the LS method (blue color) and the result of the MLS method (red color). The comparison between LS and MLS methods were carried out in Fig. 4(d), where original scanning points, fitted results by LS approach and by MLS approach were shown by green, blue and red color, respectively. Due to the global convergence performance, the LS method cannot reflect local curvature of the leaf surface. MLS can achieve partial optimal solutions of the equations, so the MLS surface fitting scheme can describe the local geometric information of foliage. Seen from the Fig. 4(e), the MLS method gives a better result than the LS method as MLS fitted results are closer to the original topological properties of real foliage surface. Finally, after leaf silhouette extraction, Fig. 4(f) gives polygon-based representations and curled meshes of leaf surface. Then the transform from discrete scanning points into 3D leaf surface was realized and visualization of Michelia and Sakura leaf by our method were achieved.

We compared the area of our reconstruction leaf model with the precise measurement value by LI-3000C. Specific comparison data was shown in Table 1. For the experimental leaves such as Michelia and Sakura tree with different size and curvature, measured results from LI-3000C and our method got similar value, which proved our method is versatile and effective enough to apply for a much larger variety of plant leaf modeling.

Table 1. Leaf area estimation from meter and our 3D model.

	Number of tetrahedron composing leaf model	Area of the reconstruction leaf model	Leaf area using LI-3000C	Deviation between two methods
Michelia leaf	Mesophyll (3212) Vein (487)	61.13 (cm^2)	63.03 (cm^2)	3.02 %
Sakura leaf	Mesophyll (879) Vein (148)	14.93 (cm^2)	15.72 (cm^2)	5.03 %

CONCLUSION

In recent years, TLS has been used for forestry parameter measurement, but the topology structure of tree is irregular. The scanning results always be interfered by external environment, such as wind and illumination variation, so deviation often exists in the scans and results in failing to capture accurate 3D structural information of forest stands. Meanwhile, TLS using LiDAR popular tools is capable of producing 3D PCD about scanning trees, but extracting structural and biophysical parameters directly from discrete PCD is a problem to be solved.

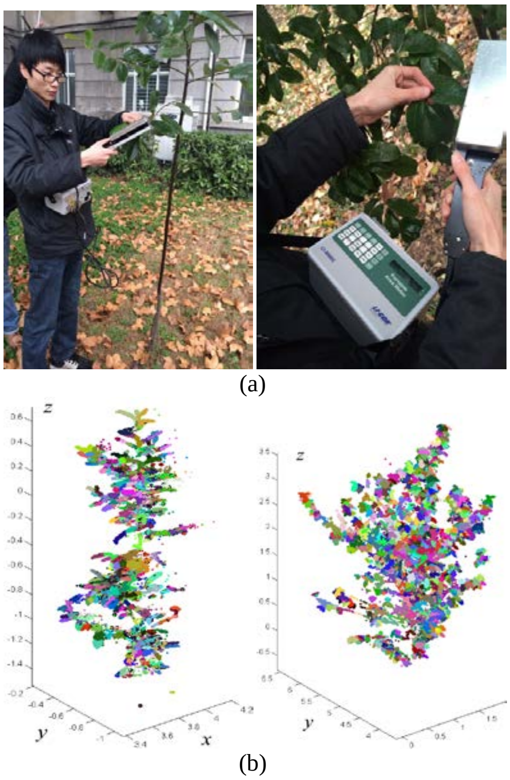

Fig. 3. Schematic to illustrate the (a) practical experiment using LI-3000C portable area meter and (b) separation of each leaf using 3D watershed method from scanned data.

In this paper, we have used computer graphics and vision theory to quantitatively identify the tree structure and accomplished the foliage surface reconstruction from discrete PCD. The main contributions of our research were as follows:

1) We demonstrated the feasibility of recovering fine-scale plant structure in 3D point clouds using features extraction and pattern recognition theory. The proposed feature extraction method employs a combination of color, shape, normal vector distribution and normal vectors of tangent plane to model the local neighborhood about given 3D point in terms of its spatial distribution. Consequently, the dimensionality of PCD features reduced by SLLE were brought into the GMM and EM classifiers, which enabled us to label each point as the fruit (isotropic distribution), leaf (planar) or branch (linear). Our experiment results on different tree PCD show that our method can automatically detect tree leaves and branches with high accuracy.

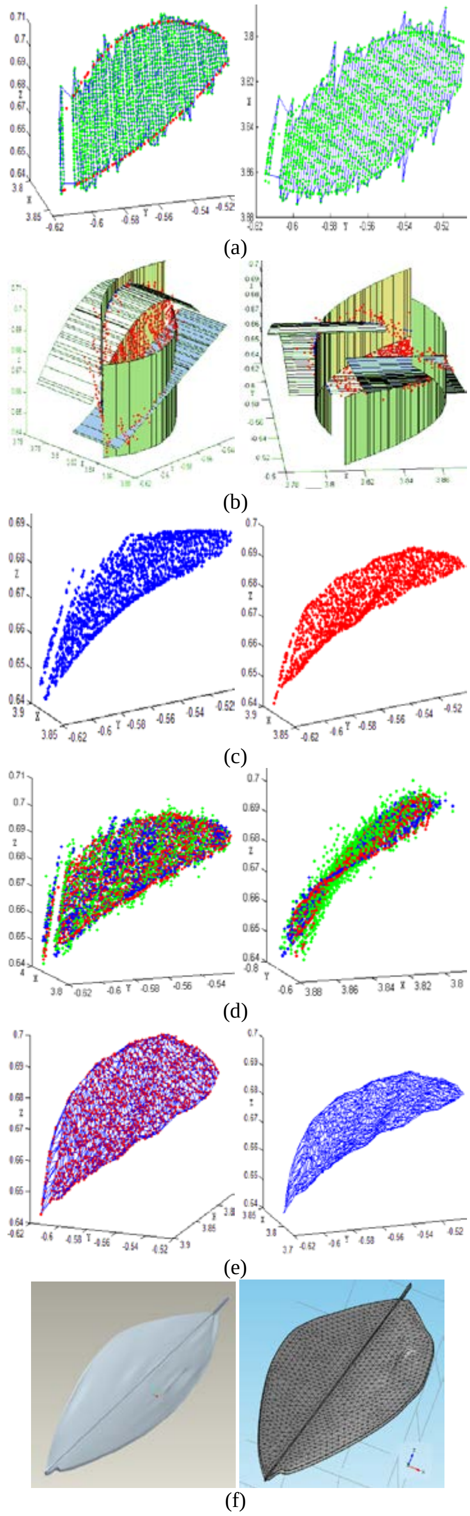

Fig. 4. Different stages of foliage surface reconstruction through our method. (a) Original scanned points of one leaf, which shows linear arrangement on X-Y plane. (b) Smooth edge points generated through the binary polynomial fitting. (c) The points with blue and red color are the fitted results through LS and MLS, respectively. The points in green color are the original scanned points. (d) Visualization results through LS and MLS processing from different viewpoints. (e) Triangulation based on the LS and MLS fitted points. (f) Final construction model of 3D foliage surface using our method.

2) In the multi-location scanning process of TLS, foliage jittering in the wind and perspective occlusion always occurred to lead to inadequately representation of target object surfaces. Thus, scanned PCD can not reflect integrated information of real canopy leaves. In our work, the bilateral edge points of foliage elements were extracted through calculation of bilateral endpoints of spatial lines, which were arranged along with the scanning angle of TLS increasing. Based on these extracted edge points, polynomial curve fitting method was adopted to obtain two fitting surfaces with original Y magnitude. Consequently, the intersection algorithm of this two fitting surfaces was proposed to determine smooth foliage silhouette. For the inner points of leaf surface, MLS approach was designed to remove deviation caused by tree joggling in wind and preserve the localized biologic deformation characteristics. Finally, Delaunay triangulation algorithm was designed to realize the transform from the discrete PCD into real leaf surface.

In brief, this paper used the latest measurement technology (TLS) to extend the traditional approaches of tree index acquisition. The main contributions include combining pattern recognition theory to identify different plant organs and accurate leaf surface reconstruction based on the computer graphics technique. After this subject study, we can provide more useful information about canopy structure and enhanced the capability of terrestrial LiDAR for characterizing forest canopies. With further development of our methods for extracting biophysical and ecological parameters from TLS data sets, long-term forest ecosystem monitoring will benefit from our techniques assuring data for sustainable forest management practices.

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ИЗПОЛЗВАНЕ НА ТОЧКОВИ ДАННИ В ОБЛАК ЗА КЛАСИФИКАЦИЯТА НА ОРГАНИТЕ И РЕАЛНИЯ СТРОЕЖ НА ЛИСТАТА НА ДЪРВЕТА

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(Резюме)

Наземното лазерно сканиране (TLS) позволява лесното и бързо събиране на точкови данни в облак (PCD) от различни обекти и се използва масово. Дърветата обаче имат съществено не-регулярна и сложна морфология и сканирането винаги ще бъде повлияно от външни промени и ефекти на включване. Затова количественото определяне на 3D морфологията и оценката на параметрите в горите чрез TLS е предизвикателство. За да решим този проблем, ние приложихме компютърна техника за подобряване на наземното лазерно сканиране (TLS) за измервания в горска среда. Предложени са нови PCD-вектори, включително форма, ориентация, нормално разпределение на векторите и нормалните вектори в равнината на тангентите и алгоритъм за контролирано локално линейно включване (SLLE). Гаусов смесен модел (GMM) е възприет за намаляване размерността на задачата, както и PCD-класификацията. Така ефективността на алгоритъма е подобрена и различни органи на дърветата се идентифицират. Освен това, методът за моделиране на листата използва полиномиална апроксимация и с „подвижните най-малки квадрати“ (MLS) се описват истинските силуети на листата, избягват се случайнипетна, водейки доточна реконструкция на сложната повърхност на листата. Подробните експерименти показват, че разпознаваемостта остава по-висока от 87.51 %, като нашият метод е приложен за различни PCD на дърветата, а точната 3D-морфологична реконструкция на листата дава подобна площ на ръчно определените по LI-3000C–методика. Така нашият метод дава обещаващи резултати за използването на TLS като ефикасно средство за намиране на параметри на растенията.