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Simulation of multi-platform LiDAR for assessing total leaf area in tree crowns

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ABSTRACT

LiDAR (Light Detection and Ranging) technology has been increasingly implemented to assess the biophysical attributes of forest canopies. However, LiDAR-based estimation of tree biophysical attributes remains difficult mainly due to the occlusion of vegetative elements in multi-layered tree crowns. In this study, we developed a new algorithm along with a multiple-scan methodology to analyse the impact of occlusion on LiDAR-based estimates of tree leaf area. We reconstructed five virtual tree models using a computer graphic-based approach based on in situ measurements from multiple tree crowns, for which the position, size, orientation and area of all leaves were measured. Multi-platform LiDAR simulations were performed on these 3D tree models through a point-line intersection algorithm. An approach based on the Delaunay triangulation algorithm with automatic adaptive threshold selection was proposed to construct the scanned leaf surface from the simulated discrete LiDAR point clouds. In addition, the leaf area covered by laser beams in each layer was assessed in combination with the ratio and number of the scanned points. Quantitative comparisons of LiDAR scanning for the occlusion effects among various scanning approaches, including fixed-position scanning, multiple terrestrial LiDAR scanning and airborne-terrestrial LiDAR cross-scanning, were assessed on different target trees. The results showed that one simulated terrestrial LiDAR scan alongside the model tree captured only 25–38% of the leaf area of the tree crown. When scanned data were acquired from three simulated terrestrial LiDAR scans around one tree, the accuracy of the leaf area recovery rate reached 60–73% depending on the leaf area index, tree crown volume and leaf area density. When a supplementary airborne LiDAR scanning was included, occlusion was reduced and the leaf area recovery rate increased to 72–90%. Our study provides an approach for the measurement of total leaf area in tree crowns from simulated multi-platform LiDAR data and enables a quantitative assessment of occlusion metrics for various tree crown attributes under different scanning strategies.

1. Introduction

Leaves are the dominant exchange surfaces of plants. The leaf area of each tree is a primary physiological and biogeochemical determinant of its overall rates of photosynthesis, carbon uptake and transpiration (Boegh et al., 2002). Variation in leaf area among trees substantially alters the output of ecological models (Chen et al., 2005). Therefore, accurate estimates of the leaf area of tree crowns are required to understand the ecosystem functions provided by trees. However, leaf area remains a difficult parameter to measure, especially in complex tree crowns such as forests. There are few reliable non-destructive methods for obtaining high-quality measurements, whereas destructive methods are too time consuming to be widely applied.

LiDAR (Light Detection and Ranging) offers an opportunity to

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conduct measurements of vegetation from different viewpoints at finer resolutions than have previously been available. Commercially available equipment, such as terrestrial (Lu et al., 2014), ground vehicle-loaded (Asvadi et al., 2016) and aerial laser scanning (Liu et al., 2017) devices, can rapidly generate point cloud data that can be used to reconstruct the 3D structure of vegetation. The fine characterization of morphological features of broad-leaf trees acquired via bottom-up or top-down scanning allows tree crowns, trunks, branches, twigs and often even leaves, to be easily distinguished through visual inspection. These high-resolution structural measurements provide an exciting opportunity to directly capture leaf area.

A number of approaches were developed to process LiDAR point clouds and estimate the leaf area of tree crowns in recent years. Based on the gap fraction theory (Nilson, 1971) and probabilistic approaches, many theoretical models were developed, including (i) a maximum likelihood estimator combined with a Poisson gap model to estimate gap fraction and leaf area index (Zhao et al., 2015), (ii) calculation of the contact frequency within each voxel to estimate gap fraction and correct for the influence of occlusion effects on the leaf area estimate (Li et al., 2017), (iii) the use of multi-return LiDAR data to evaluate laser penetration metrics through the tree crowns and to compute the gap fraction inversion (Alonzo et al., 2015), (iv) determination of the canopy extinction coefficient of foliage elements by considering both inclination and azimuth angles of leaves from different laser scanning data (Ma et al., 2017) and (v) the development of a 3D modelling framework of forest stands to quantify within-crown clumping factors and to evaluate the gap fraction of tree crowns (Woodgate et al., 2015). These previous studies were based on optics theory, which considers laser hits to be a complete sample. The number of laser returns within a given zenith angle range is used to estimate the gap probability within the tree crown, from which the leaf area index (LAI) can be computed.

Despite the recognized advantages of LiDAR techniques, the analysis of complex point clouds and the extraction of metrics relevant to ecology and environmental science still face practical challenges. A persistent problem with the direct measurement of LAI is occlusion in dense tree crowns caused by multiple overlapping leaf surfaces and branches. Thus, any method should compensate for leaves that are not visible from the perspective of the laser position (Côté et al., 2012; Van der Zande et al., 2011). When developing an algorithm to retrieve leaf area estimates, it is essential to incorporate measures of uncertainty related to the presently unquantifiable issue of signal occlusion. The representation of a scanned tree as a discrete set of points is also difficult to relate directly to the leaf surface area (Yun et al., 2016). The spatial resolution of scanned points is inversely proportional to the acquisition distance (Méndez et al., 2013; Pesci et al., 2011), which means that a higher density of scanned points will be acquired when foliage is closer to the scanner, leading to a non-uniform resolution of canopy structures. During the scanning process, wind blowing on the leaves and the intrinsic properties of the sensors cause noise in the scanned data, which complicates the characterization of tree crown attributes.

Computer graphics (Watt and Watt, 2000) provide 3D representationof geometric data is another approach used for performing feature calculations and rendering 3D models, which are used to accurately describe complex, non-rigid and irregular objects, such as bunch grasses, trees and forests. Computer graphical methods combined with computer vision and image processing methods have been applied to retrieve forest properties and extract the key parameters from the scanned data. These methods include irradiation geometry to analyse the radiation regime in a forest canopy and measurement of the gap fraction of forest plots (Van Leeuwen et al., 2013), 3D triangulation to produce a geometrically explicit description of a forest canopy from airborne point cloud data (Vauhkonen et al., 2016), point cloud-based triangulation for laser–leaf intersection points for the rapid measurement of the 3D distribution of leaf orientation and leaf angle probability density (Bailey and Mahaffee, 2017), graphic projection strategies related to the tree point cloud to deduce tree row scanned volume and leaf area (Sanz et al., 2018), individual leaf segmentation and 3D leaf surface reconstruction to characterize the morphological properties of agricultural plants (Chaivivatrakul et al., 2014), and leaf area and height estimation using geometric features from sparse 3D points generated from stereovision models (Lati et al., 2013).

The main objective of the present study was to develop a computer graphic-based methodology to quantify leaf area and the occlusion effect for different LiDAR scanning patterns. This aim was achieved by developing a computer graphics algorithm to extract the total leaf area covered by simulated multi-platform LiDAR point clouds and by implementing a computer reconstruction technique to validate the results. The specific objectives were: 1) to generate 3D virtual tree models obtained from field measurements and to design a simulation algorithm to conduct virtual laser scanning of the trees; 2) to develop a computer graphics-based approach for calculating total leaf area covered by laser beams from discrete LiDAR point clouds using Delaunay triangulation with an adaptively chosen threshold; and 3) to assess different stratified strategies of scanned points combined with the defined ratio of point number per unit leaf area for evaluating the occlusion effects on the leaf area retrieval corresponding to different scanning patterns (i.e., fixed-position scanning, multiple terrestrial scanning combination and aerial-terrestrial cross-scanning). Through this we provide and validate a novel method for direct leaf area estimates based on the point cloud coverage under a range of scanning scenarios.

2. Materials and methods

2.1. Field data

Five datasets comprising one mango tree (*Mangifera indica* L.), two rubber trees (*Hevea brasiliensis* Müll.Arg.), one walnut tree (*Juglans* X *intermedia.*) and one apple tree (*Malus communis* Desf.) were obtained from Sinoquet et al. (2009). All samples were isolated trees with no crown contact. The 3-year-old walnut tree was grown in a research field at the INRA Research Centre in Clermont-Ferrand, France. The two-year-old mango tree was grown in an orchard in Ban Bung, near Chonburi, Thailand. The smaller 2-year-old rubber tree was grown in the garden of the Department of Agronomy Kasetsart University, Bangkok, Thailand. The larger 5-year-old rubber tree was grown at the Suwan Wajokkasikit Field Crops Research Station, Pak Chong, Thailand. The 20-year-old apple tree was located on a private property in Vouvray, near Tours, France. The spatial coordinates and the orientation angles of every leaf, which were in the form of the midrib azimuth and inclination angles, and the rolling angle of the leaf lamina around the midrib were collected with a 3D electromagnetic digitizer (Sinoquet et al., 2009). Leaf dimensions were measured manually. The tree height varied from 1.7 to 10.2 m, and the number of leaves varied from 895–26,254, yielding total leaf areas of 4.07–35.2 m^2. A summary of these architectural data is provided in Table 1.

2.2. Creation of tree models

2.2.1. Creation of 3D tree crown models and discretization

Three-dimensional models based on the *in situ* measurements were created for each selected tree. The length l_s and width w_s of the s th leaf surface were used to approximate the leaf as a symmetrical ellipse on each side of the midrib; the initial position of each leaf surface lies on the X–Y plane, and the normal vector of the leaf surface in 3D space is $\overrightarrow{h_s} = (0, 0, 1)$. A uniform sampling strategy was adopted to obtain a set of valid points defining whole leaves. The sampling spacing of the points on each leaf surface was equal to the size of a grid cell c, set here as 0.4 cm (Fig. 1a). Then, for every leaf in the total set of leaves, the set of points $P_s(x_{i,j}, y_{i,j}, z_{i,j})$ was used to define the sampling point of the i th row and the j th column on the s th leaf surface. Given the overall leaf

Table 1
Attributes of trees, such as height, crown diameter, number of leaves, total leaf area of the tree crown, were collected manually by (Sinoquet et al., 2009) and were used for laser scanning simulations. The tree crown volume, tree crown projection area, Leaf Area Index, average area of each leaf and sampling points on the vegetative elements were calculated from these data.

	Walnut	Mango	Rubber 1	Rubber 2	Apple
Height (m) Crown diameter (m)	3.9 1.8	1.7 1.8	2.2 1.6	10.2 4.1	8.3 5.6
Total number of leaves	1558	1636	895	12141	26254
Total leaf area of the tree crown (m^2)	7.07	6.56	4.07	35.10	37.41
Basal diameter (cm)	5.18	7.67	4.47	14.08	12.58
Total number of sampling points on leaf surfaces	533,007	535,142	308,077	2,780,905	3,077,374
Total number of sampling points on branch surfaces	120,490	198,831	162,325	596,843	1,077,981
Tree crown volume (m^3)	3.20	1.36	1.32	23.08	36.95
Tree crown projection area (m^2)	1.82	1.43	1.92	10.58	12.98
LAI (leaf area index)	3.89	4.58	2.12	3.32	2.88
Average area of each leaf (cm^2)	45.38	40.10	45.47	28.91	14.25

properties assessed with rotation angles θ_s^x, θ_s^y and θ_s^z around the X axis, Y axis and Z axis, respectively, and the spatial location $d_s(d_s^x, d_s^y, d_s^z)$, the composite transformation of the original points $P_s(x_{i,j}, y_{i,j}, z_{i,j})$ in the X, Y plane was represented as follows:

$$P_s^r(x_{i,j}^r, y_{i,j}^r, z_{i,j}^r) = P_s(x_{i,j}, y_{i,j}, z_{i,j}) \times R_X \times R_Y \times R_Z \tag{1}$$

New points $P_s^r(x_{i,j}^r, y_{i,j}^r, z_{i,j}^r)$ were thus generated to represent the position, size and shape of each individual leaf (Fig. 1b). After the transformation, the new normal vector of the transformed leaf surface was adjusted to $\vec{h}_s^r = (h_{s,x}^r, h_{s,y}^r, h_{s,z}^r) = \vec{h}_s \times R_X \times R_Y \times R_Z$, where

$$R_X = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\theta_s^x) & \sin(\theta_s^x) \\ 0 & -\sin(\theta_s^x) & \cos(\theta_s^x) \end{bmatrix}, R_Y = \begin{bmatrix} \cos(\theta_s^y) & 0 & -\sin(\theta_s^y) \\ 0 & 1 & 0 \\ \sin(\theta_s^y) & 0 & \cos(\theta_s^y) \end{bmatrix} \textit{and } R_Z = \begin{bmatrix} \cos(\theta_s^z) & \sin(\theta_s^z) & 0 \\ -\sin(\theta_s^z) & \cos(\theta_s^z) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Therefore, the equation of the s th leaf surface plane can be simplified as follows:

$$h_{s,x}^r(x^r - d_s^x) + h_{s,y}^r(y^r - d_s^y) + h_{s,z}^r(z^r - d_s^z) = 0 \tag{2}$$

where $[x^r, y^r, z^r] = [x, y, z] \times R_X \times R_Y \times R_Z$ and $x \in [-l_s/2, l_s/2]$, $y \in [-w_s/2, w_s/2]$ and $z \in [-0, 0]$. The range of x^r, y^r and z^r can be deduced from the range of variables x, y and z representing the initial ellipse lying on the X–Y plane. All leaves together constituted a

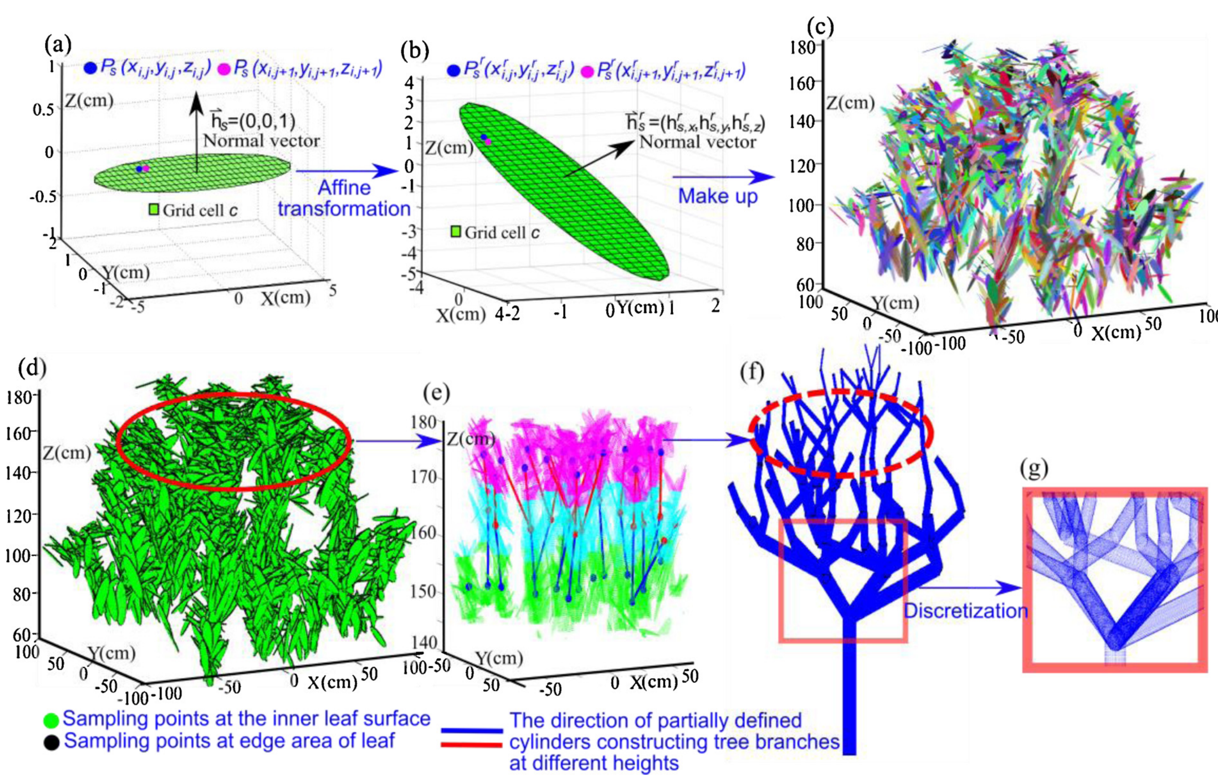

Fig. 1. Schematic illustrating a tree (mango tree) reconstruction. (a) Initial sampling points of one mango leaf on a plane of the elliptical form. (b) Spatial position and inclinational and azimuthal angle of leaf attributes through affine transformation. (c) Numerous leaves with various attributes make up the three-dimensional model of the mango tree crown. (d) Sampling points covering each leaf surface make up the tree crown model; the green points represent the sampling points at the inner portion of leaf surface, and the black points represent the edges of each leaf. (e) The red and blue lines represent the directions of cylinders constituting the tree branches guided by field measurements. (f) Overview of the reconstructed 3D tree skeleton. (g) Close-up of partial virtual branch discretization for obtaining branch sampling points. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

complete representation of the tree crown (Fig. 1c and d). The leaf area of the tree crown was determined by summing the ellipse area of each leaf surface.

2.2.2. Creation of tree branches and discretization

For all target trees, prior information of each main branch obtained from successive measurements was used for tree branch construction. Branching, branch diameter, and flush order were given as well as the precise ranking of leaves along each branch (Sinoquet et al., 2009). A 3D pipeline mode reconstructed each branch from the proximal to distal tip until the whole branching architecture was retrieved for each target tree. Thus, the preliminary tree skeleton was delineated, and a set of generalized cylinders was assembled into a skeleton along connected vectors to form the tree branches (Fig. 1e). The radii of cylinders, set as the diameter of the branches, were smaller at the upper tree crown and larger at the lower tree crown. Finally, a uniform sampling strategy with sampling spacing c (equal to the size of a grid cell) was performed to transform every branch cylinder into discrete points $P_b(x_{i,j}^b, y_{i,j}^b, z_{i,j}^b)$ (Fig. 1f and g). Finally, the tree model and corresponding discrete point set $P_i = \{x_{i,j}^r, y_{i,j}^r, z_{i,j}^r, x_{i,j}^b, y_{i,j}^b, z_{i,j}^b\}$ were made available for the laser scanning simulation.

2.3. Laser scanning simulation and scanned leaf area calculation

After the tree models were reconstructed and the vegetative elements were transformed into high-density sampling points, a rapid simulation method based on the line-point intersection principle was proposed to perform various laser scanning patterns, including single or multi-angle terrestrial laser scanning (TLS) and aerial laser scanning (ALS), and to acquire the corresponding scanned points of each tree model. To calculate the scanned leaf area and to evaluate the occlusion effect on laser scanning, every modelled tree crown was divided into six layers according to the scanning distance regarding various scanning patterns, and a triangulation method with automatic adaptive threshold selection was designed to transform the discrete scanned points into the leaf surface (Supplementary materials S1). The threshold was determined based on the scanning angular resolution, distance between the leaf and scanner, and angle between the incident laser beam and the normal vector of the leaf surface. Then, the ratio ρ_z between the number of scanned points and corresponding scanned leaf area in each layer was calculated to deduce the scanned leaf area of each layer from various scanning patterns. To compare with the true leaf area, a quantitative assessment of the occlusion metric for various tree crown attributes under different scanning patterns was then performed. The flowchart of our method is shown in Fig. 2, and the detailed descriptions of technical implementation are supplied in the Supplementary materials section S1.

Five tree crowns were taken as the subjects for scanning simulations, and virtual scans of each tree crown were conducted from either one TLS position or three TLS positions around the tree, with an ALS position also included. Various laser scanning simulation scenarios were conducted using our program. The scanned targets in our experiments can be either leaves alone (without branches) or leaves and branches together (with branches). Scanning simulation scenarios either with or without occlusion were also tested. In the former scenario (with the occlusion effect), only the nearest intersection point on each beam to the scanner was identified as the scanned point (i.e., the simulation based on the real process of scanned data acquisition). In the latter scenario (without the occlusion effect), every beam could pass through all vegetative elements and all intersection points between each beam and scanned vegetative elements were identified as the scanned points, i.e., a hypothesis that occlusion does not exist in the scanning process. Under the four scenarios indicated above (i.e., without branches, with branches, with occlusion and without occlusion), the leaf area retrieved in each layer from the scanned points was compared with the true leaf area directly calculated from the tree models (Section 2.2). Major parameters and the proportion of true leaf area detected are summarized in the following sections. Our laser scanning simulation method was implemented in MATLAB (The MathWorks, Inc. Natick, Massachusetts, U.S.A.), and the code can be requested from the first author. Execution of one scan simulation program takes approximately 3 min for a small tree and approximately 7 min for a large tree. The running time of our program is similar to that of a real scan accomplished using a Leica C10 scanner.

3. Results

3.1. Horizontal penetration of virtual scans

We focus first on data collected from the mango tree as an illustration of the overall pattern before comparing the results for different tree crowns. Horizontal scanning profiles reveal the degree of signal attenuation through the tree crown and, hence, the accuracy of the leaf area estimation (Fig. 3). These profiles also reveal the relative degree of occlusion with one versus three scanning positions. Fig. 3a shows a lateral snapshot of one scanning pattern in which different colours represent the degree to which each scanned point blocks the vegetative elements behind the point. The leaf elements closer to the scanner block more subsequent vegetative elements for each laser beam than the more distant leaf elements, and the missed points are further from the scanner. The number of scanned points detected per unit leaf area measured, ρ_z, and the total leaf area of each segment were calculated and are illustrated in Fig. 3b and 3c respectively. The ρ_z estimated from the original leaf points using our Delaunay method is close to the initial sampling resolution, with discrepancies caused by the difference between true and estimated leaf area. Without occlusion, there is a decline in ρ_z with distance that is caused by the beams spreading out in space. When perspective occlusion is included, the overall values of ρ_z are lower due to the smaller overall number of scanned points. Moreover, when the branches are assembled into the tree crown, ρ_z is slightly smaller than its value without branches because more leaf elements in the distant part of the tree crown from the scanner are blocked by the branches. The leaf area estimation using our method is shown in Fig. 3c.

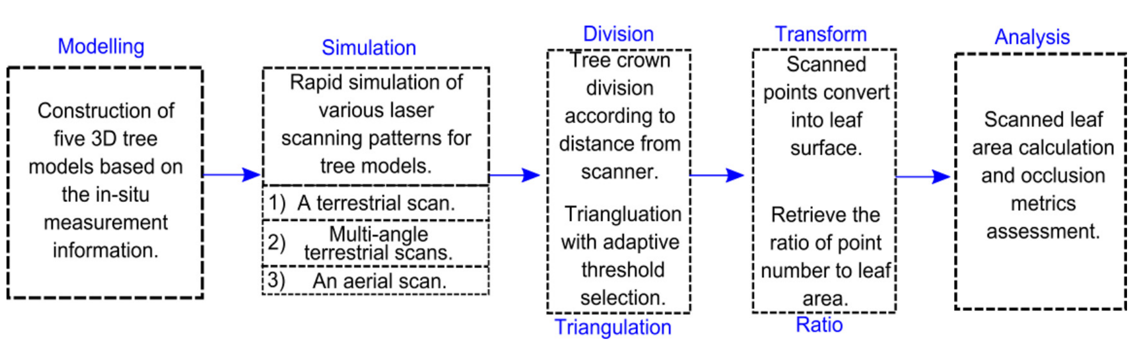

Fig. 2. The flowchart illustrating the main steps of our simulation method.

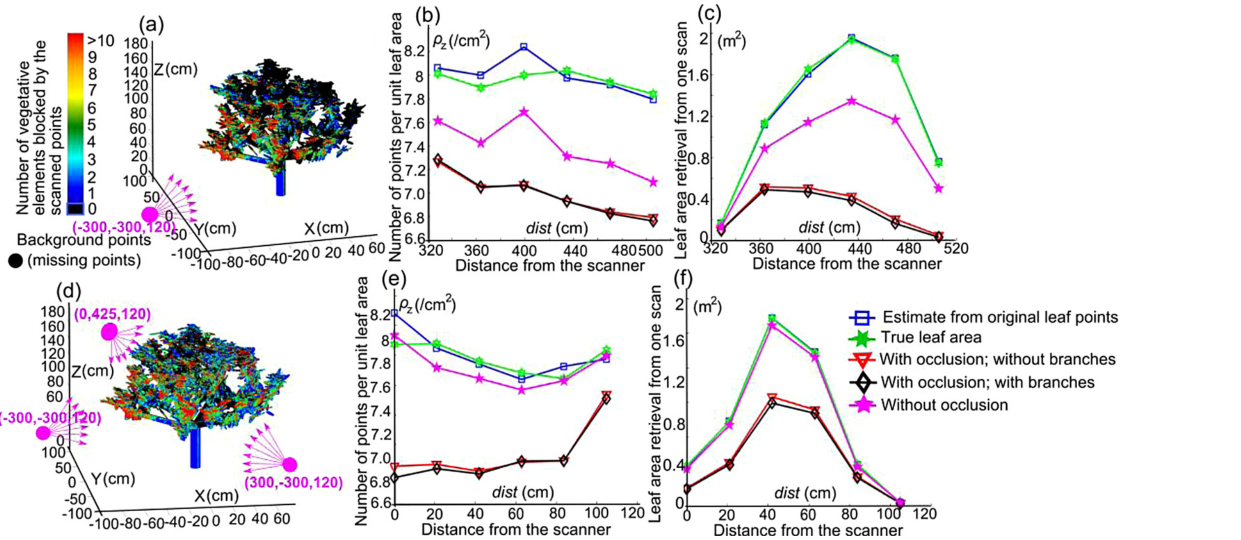

Fig. 3. Horizontal scanning profiles representing the ratio ρ_z (number of scanned points per cm^2 leaf) and retrieved leaf area distribution from the mango tree model. (a) Observed from a perspective view, the mango tree is represented by one virtual scan, where different colours represent the degree to which each scanned point blocks subsequent vegetative elements for each beam, and black represents missing points, which are the occluded points further from the scanner. (b) The calculated ratio ρ_z of different segments. (c) The horizontal profiles of leaf area captured by a single scanner. (d) Scanning pattern of three scanners around the target tree. Although from an external viewpoint it appears that comprehensive laser coverage of the tree crown has been obtained, occlusion remains in the centre of the tree crown due to blocking by outer foliage elements. (e) and (f) are equivalent figures to (b) and (c) from three scanning positions represented as distance from the tree crown centre.

From the original sampling points of leaf surfaces, the estimated results using our Delaunay triangulation method (represented by the dashed blue line with square markers in Fig. 3) converge on the true leaf area, demonstrating the effectiveness of our leaf area retrieval method. When occlusion is incorporated, the reduction in leaf area retrieval highlights the effect of vegetation closer to the scanner blocking other vegetation. In the sections of tree crown closest to the scanner, almost no effect of occlusion is evident. On the distal side of the tree, only a small proportion of the total leaf area is captured. When the branches were included in the tree crown, the occlusion effect increased slightly, resulting in a decline in estimated leaf area.

Substantial improvements were realized when three TLS positions around the model tree were employed (Fig. 3 d). In such a set-up, the occluded points exist mainly in the tree crown centre. Thus, division of the model tree into six annulus sectors according to the distance from the tree crown centre was conducted to assess ρ_z and total leaf area of each segment. Based on the original sampling points of the leaf surface, a distribution of ρ_z across the tree crown was created with values similar to the initial sampling resolution (Fig. 3e). In the three terrestrial virtual scans around the tree crown with occlusion, the overall values of ρ_z are lower and increase with distance from the tree crown centre because the leaf elements in the tree crown centre are blocked by outer foliage elements. Thereby, 62.64% of the total leaf area of the model tree was represented by the black line in Fig. 3f. When occlusion is excluded, ρ_z reaches a theoretical maximum value in the inner portion of the tree crown, where the leaves could potentially be scanned from multiple positions. It increases again at the crown edge near the scanner. Fig. 3f also shows that including tree branches has only a slight impact on the overall accuracy of the total leaf area assessment.

3.2. Vertical penetration of virtual scans

The walnut tree is taken as an illustration to reveal the relative degree of occlusion with one versus three TLS positions. Further information on the performance of TLS in occluded structures is predicted by examining estimated leaf area across the vertical profile of the tree crown (Fig. 4). The tree crown was divided into six equal-height segments from the lowest to highest detected leaves. ρ_z and the total leaf area of each segment were calculated under various scanning patterns. A similar analysis to that seen in the horizontal virtual scans in Fig. 3 was conducted but with some important differences. Fig. 4a, b and c show the scanning pattern of a single terrestrial scanner alongside the target tree. The majority of laser beams are blocked by the tree crown elements at lower heights. Therefore, occlusion increases with the height of the tree crown, and there is a declining trend of ρ_z with increasing distance from a height of 1.2 m (Fig. 4b). Following the conversion into leaf area estimates (Fig. 4c), a recovery of 60.09% of total leaf area was achieved for the walnut tree crown without occlusion, but the recovery of TLA with occlusion decreased to 32.50% or 37.28% with or without branch occlusion, respectively. The use of a single virtual scan therefore captures only a minority of the leaf area, rendering the accurate estimation of tree crown properties impossible.

The combination of data from three scanning positions around the tree crown reveals similar patterns of ρ_z with height (Fig. 4e), and the un-scanned vegetative elements exist solely in the centre of the upper tree crown. The point density is highest at lower positions in the tree crown, resulting in a marked improvement in the recovery of true leaf area (Fig. 4f). In the absence of occlusion, almost the entire tree crown can be reconstructed and nearly 97.41% of the tree crown leaf area is retrieved. When occlusion is incorporated, 72.69% of the tree crown leaf area is detected with and 75.11% without branch occlusion, which is markedly higher than that from a single scanning point.

3.3. ALS simulation with occlusion

As shown in the previous sections, the scanning process yields a lower leaf area estimate for the model trees when occlusion is present in the centre and higher parts of the tree crown. This result is due to localized high densities of leaves in the outer and lower parts of the tree crown that are more impenetrable to the laser beams. Thus, a new scanning pattern that included three ground-based virtual scans around a target tree and a virtual scan overhead at a given height was employed to simulate combined TLS and ALS for leaf area retrieval and occlusion quantification. Rubber tree 1 is taken as an example with a scanning pattern similar to that described above but with the inclusion of a newly added aerial virtual scan to predict leaf area captured from

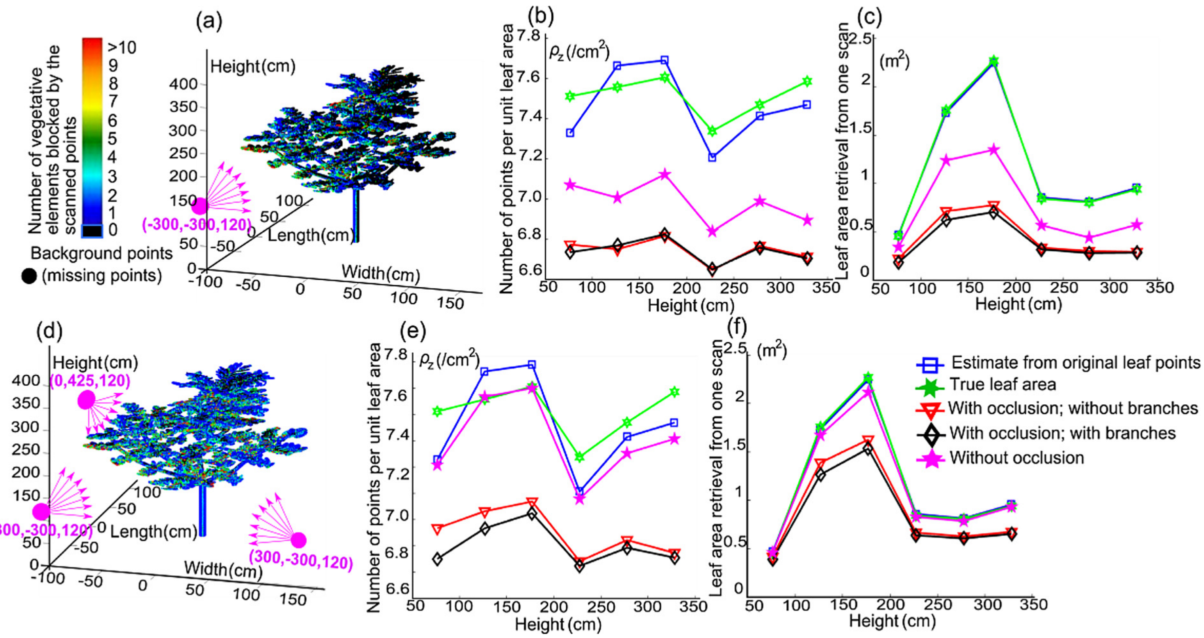

Fig. 4. Visualization of the results of the scanning analysis for the walnut tree, which is separated into six layers of equal height with and without occlusion, with and without branches and compared with true leaf area. (a) The tree is scanned from one TLS position, and the degree to which each scanned point blocks vegetative elements located behind the point for each beam is represented by different colours. (b) Ratio ρ_z of each height band derived from a single virtual scan decreased with increasing height. (c) Leaf area profiles of each vertical segment from a single virtual scan. (d, e and f) are equivalent figures to (a, b, c) for three TLS positions.

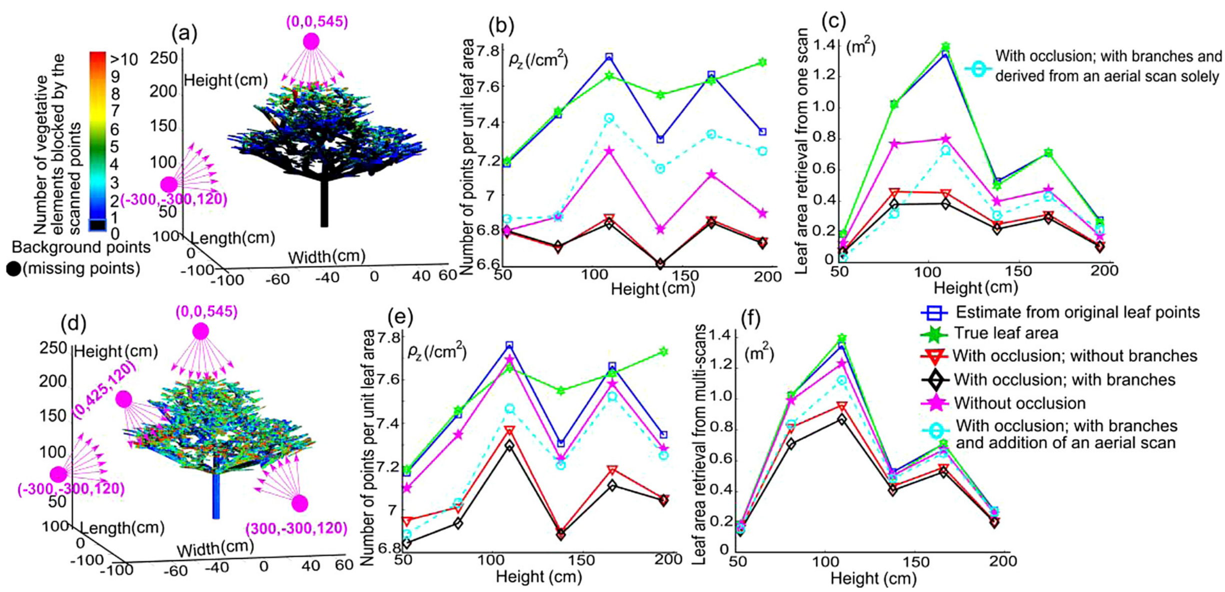

Fig. 5. Visualization of scanning results for rubber tree 1, including the addition of an aerial virtual scan, analysed in the same manner as in Fig. 4. (a) Laser beam intercepted by vegetative elements from an aerial scanner. (b) Ratio ρ_z of each height band from either a terrestrial or aerial virtual scan. (c) Profiles of leaf area retrieval for each vertical segment from a single terrestrial or aerial virtual scan. (d, e and f) are equivalent figures for the three ground-based virtual scans and with the addition of an aerial virtual scan.

both TLS and ALS-based data. The results are shown in Fig. 5. An aerial virtual scan is obtained from the overhead position at point (0, 0, 5.45 m). Fig. 5a shows that substantial occlusion dominates at lower heights of the tree, and the upper leaves of the tree crown intercept the majority of the laser beams. The light blue dashed line with circular marks in Figs. 5b and c represents the ρ_z and retrieved leaf area distribution from an aerial virtual scan only. Occlusion decreases at greater heights, and the value of ρ_z increases with increasing distance from the ground. The vertical profile of leaf area retrieval from an aerial virtual scan (Fig. 5c) shows that a higher deviation of leaf area estimation occurs at lower heights of the tree crown. In total, 49.28% of the total leaf area is recovered from an aerial virtual scan, which is larger than the 40.51% of the leaf area captured from the lateral virtual scan because the tree crown structure allows light to penetrate more deeply into the tree crown from the zenith position. Occlusion is effectively alleviated when the three terrestrial virtual scans and one aerial virtual scan are combined. Thus, occlusion occurs almost entirely inside the tree crown (Fig. 5d). Fig. 5e shows a greater ρ_z distribution in the upper tree crown (light blue dashed line) than that in the derivation from only three terrestrial virtual scans around the tree crown (black line) because vegetative data retrieval is always deficient from the overhead position when only TLS is adopted. The final leaf area retrieval with

Table 2
Percentage of the total leaf area recovered when tree crowns were scanned at one or three ground-based scanning positions, with (+) or without (-) branches, with (+) or without (-) occlusion and with or without the supplement of an aerial virtual scan. The final row shows the effectiveness of the triangulation algorithm in reconstructing virtual leaf area from the simulated points.

			Walnut	Mango	Rubber 1	Rubber 2	Apple
Scanning and algorithm parameters	Distance from tree crown centre to scanner (m)		4.35	4.26	4.14	7.70	6.69
	Angular resolution (degree)		0.0345	0.0345	0.0345	0.0222	0.0222
	Calculated threshold ζ (cm)		1.992	1.947	1.897	2.275	1.974
	Branch	Occlusion	Retrieved leaf area from scanned data (percentage)				
One (TLS)	+	+	32.50	24.19	38.73	27.64	33.25
	–	+	37.28	27.58	40.51	30.12	35.26
	–	–	60.09	66.79	67.74	56.19	65.84
One (ALS)	+	+	40.39	32.52	49.28	32.20	37.92
Three (TLS)	+	+	72.69	60.76	73.39	59.03	63.51
	–	+	75.11	62.64	76.61	61.15	67.05
	–	–	97.41	96.43	95.77	94.35	96.33
Four (3TLS + ALS)	+	+	86.64	72.04	90.08	75.99	80.75
Original points			100.46	98.76	100.18	99.62	99.89

comprehensive scanned data coverage (three terrestrial virtual scans and one aerial virtual scan added) shown in Fig. 5f reaches 90.08%, which is higher than the 73.39% leaf area retrieval when using only three registered TLS-based virtual scans. The discrepancies in leaf area retrieval between the two scanning patterns become larger with increasing height of the tree because a tall tree decreases the proportion of leaf elements captured from ground-based scanning positions.

3.4. Comparison of simulation results for different trees

The simulations of the five different trees allowed comparisons of the effectiveness of leaf area recovery. The crowns and branches of different trees varied markedly in height and diameter as well as in the number and total area of leaves (Table 1). In Table 2 we present the overall leaf area recovery for each tree based on point clouds assembled from one or three ground-based virtual scans with and without occlusion, with and without branches, and with the addition of an aerial virtual scan. The threshold of triangulation for the scanned leaf area calculation is derived from the Supplementary materials section 1.3.

Combining the biological properties of the tree crown shown in Table 1 and our simulation scanning results shown in Table 2, many conclusions were deduced as follows. The mango and walnut tree crowns have nearly the same amount of leaf material, but the mango tree has a lower height and a smaller crown than the walnut tree. As a result, the high leaf area density of the mango tree causes greater occlusion and lower leaf area recovery. Similarly, rubber tree 2 and the apple tree have much larger tree crowns and greater height than the other tree crowns, with an approximately nine-fold increase in the tree crown leaf area and number of leaves relative to any of the other tree crowns. Due to different tree properties and greater distance between the scanner and leaf elements, a finer angular resolution of TLS and ALS was set, and under these conditions the results show a similar degree of self-shading and leaf area retrieval to other tree crowns. For target trees with high angular resolution and close range scanning, with 3 TLS virtual scans around the tree crown, over 60% of leaf area can be reconstructed from the registered point cloud. This value reaches 72% for a tree with a lower LAI and smaller crown. Moreover, one overhead virtual scan (ALS pattern) always yields a higher estimation of leaf area for all tree crowns under the influence of occlusion than the leaf area estimation derived from a single TLS-based virtual scan, and the difference between the two patterns ranges from 4.6 to 10.6%. Additionally, the scanned branch elements were less influential on the ALS pattern than in the results from lateral TLS. One explanation for this difference may be that a higher probability of large inclination angles for tree crown leaves optimizes solar radiation absorption, and non-photosynthetic parts (branches and stems) are not as exposed to available light at smaller zenith angles because they are usually hidden within the tree crown. Furthermore, higher LAI and larger leaf size result in higher occlusion levels. The degree of the overall leaf area retrieval increased to 72.8–90.3% from three registered TLS-based virtual scans plus one ALS-based virtual scan. When occlusion is not incorporated, almost all leaf elements are captured from three TLS-based virtual scans around the tree crown, which allows for the extrapolation of the total leaf area near the true value from these scanned points and verifies that occlusion has a considerable impact during laser scanning data collection.

4. Discussion

4.1. Effect of occlusion on retrieved leaf area

Leaf area is one of the most important parameters in the biology of trees. Although laser scanning techniques provide detailed information on the three-dimensional structure of trees and forests, the application of laser scanning in the estimation of LAI is complicated by occlusion caused by mutually occluded vegetative elements (Ehbrecht et al., 2016). For instance, the movement of leaves due to wind will cause positional and registration errors in combined point clouds and will increase occlusion (Liang et al., 2016). Trees in forests are also surrounded by other stems and sub-canopy vegetation, which will obstruct terrestrial views. Moreover, airborne laser scanning typically occurs at greater distances and lower point resolutions than in our simulations, and potential occlusion of understory trees is generated by dominant trees and competition between tree crowns from an aerial perspective. As target trees can be scanned from different viewpoints with different point densities caused by beams spreading out in space, methods to infer vegetation leaf area from multiple scans need to account for many factors, including the distance between the target tree and scanners, the parameters of each scan, the occluded foliage elements that exist in the intermediate crown and the discrepancies in the information obtained from different scanning view points. Thus, the existing methods to estimate LAI through voxelization (Béland et al., 2014; Kükenbrink et al., 2017) require further development to quantify the impacts of the occlusion effect.

Many current approaches use the Beer-Lambert law (Woodgate et al., 2016; Zheng and Moskal, 2012) to link laser scanning beam transmittance with foliar surface density to assess LAI. However, accurate estimates of gap fraction, the clumping index of foliage and the validity of the Poisson model in complex structured tree crowns are not easily obtained. Approximations are therefore used instead of empirical values (Olivier and Robert, 2017; Woodgate et al., 2015). The difficulty in obtaining reliable reference data also hampers the validation of the approaches developed to assess leaf area and prevents both theoretical and practical issues from being effectively addressed. Direct in situ measurements of LAI are rare due to the complexity, resource requirements and cost involved in the deployment. LAI estimates are also susceptible to bias resulting from the statistical sample size of foliage obtained from tree crowns (Weiss et al., 2004).

Given these constraints, adopting a modelling framework to simulate laser scanning data for realistic vegetation is an attractive option for evaluating the impact of occlusion on leaf area assessments and performing validations. Our modelling framework, which includes vegetation architecture and various scanning patterns, represents a complementary approach for evaluating leaf area and occlusion using reliable reference data.

4.2. Suggested scanning methods to alleviate occlusion

The impact of occlusion persists in the laser scanning process to a varying extent between different target trees and scanning patterns. Hence, choosing an optimized scanning strategy to effectively alleviate the occlusion effect is helpful to increase scanned data quality and to improve retrieval of tree leaf area.

The phenotypic characteristics of trees, such as the crown shape, leaf surface properties and gap fraction distribution, are influenced by various factors that include solar radiation, water availability, soil properties, climate type and wind effects on growth. Different tree phenotypes produce different degrees of occlusion under various scanning views. For example, the maximal zenith angle of the sun near the equator places the sun more directly above plants, and for tall trees with flat crowns, more leaves are exposed when the sun is in this position (Duchemin et al., 2018). Hence, aerial scanning patterns above the tree crown can capture more leaf elements than TLS patterns. At high latitudes, the sun is relatively low in the sky, and trees in these regions tend to be cone-shaped, with leaves extending from the top of the tree to the bottom to increase the absorption of sunlight (Duchemin et al., 2018). For these trees, TLS-based scanning is a better choice to acquire leaf element information from a lateral view. Our work provides a modelling basis for establishing scanning plans depending on the phenotype of the trees.

Leaf attributes in different positions of tree crowns vary with allometric growth. 'Sun leaves' occur on the irradiated side of the tree crown, and the normal vectors of the leaf surface point almost directly at the sun to ensure direct solar radiation. 'Shade leaves' always exist in tree crowns or on the shady side of the crown where there is limited direct light. Shade leaves have non-uniform normal vectors of the leaf surface to effectively use diffuse solar radiation (de Casas et al., 2011). Hence, a scanner can be placed in a position that faces the shady side of the tree crown and another scanner can be placed facing the side exposed to direct solar radiation. Shade leaves with a non-uniform normal vector of the leaf surface closer to the scanner would allow more laser beams to penetrate the canopy and reach the other (sunny) side, where more leaf surfaces face the direction of the sun, allowing greater exposure of leaf area to the laser beams passing through the crown. In addition, trees can have asymmetric crown structures caused by long-term fixed directions of wind or neighbouring objects that show strong competition for space. In these cases, a TLS facing the side of the tree crown opposing the wind or suppressed by neighbouring objects is preferred due to a larger gap fraction and sparse leaf area density on this side, which optimizes beams passing through the crown and covering more vegetative elements across the tree.

Certain inferences can be deduced from Tables 1 and 2. High scanning resolution and multi-angle scan registration can lead to more laser beams entering the tree crown through gaps to optimize the detection of vegetation elements in the crown. Different magnitudes of LAI, tree height and tree crown volume may produce different degrees of mutually occluded vegetative elements and decrease the scanning resolution and laser scanning coverage field relative to the whole tree crown. Based on Table 2, for a small tree (height < 5 m) with a larger tree crown (> 3 m^3) and smaller LAI (< 3), three TLS positions around the tree can capture 80% of the vegetative elements and less than 20% compensation is needed for the final leaf area estimation. If the small tree has a larger LAI (> 3) and small tree crown, a greater compensation value is necessary for leaf area estimation. For tall trees (height > 5 m) with a larger tree crown (> 10 m^3) and lower leaf area (< 3), the combination of multi-TLS and ALS is preferred to obtain evenly distributed scanned points of the tree crown covering more than 85% vegetative elements in the crown. If the LAI of the tall tree is larger than 3, then more than 25% of the compensation of the leaf area estimation will likely be needed for scanned data deficiencies in the intermediate tree crown.

4.3. Application of the method

The reliability of computer simulation-based methods versus the real scanning process can be determined through a verification trial with a local tree in real world as a reference. Two devices, i.e., an electro-magnetic 3D digitiser Fastrak (Polhemus Inc., Colchester, VT, USA) and a laser scanner (Leica C10 or RieglTM VZ-400), are needed for real tree modelling and benchmark acquisition, respectively. The tree can be modelled using 3D digitizing by Fastrak (Mabrouk and Sinoquet, 1998; Sinoquet et al., 2009), and the virtual tree model can be reconstructed using the corresponding digitized leaf and skeleton information of the real tree, which is taken as the target tree for virtual scanning simulation. For reference data acquisition of TLS and ALS, the scanner can be placed alongside or fixed atop a high place to provide lateral or top-down scanning for the target tree, respectively. The restored virtual scanning scene using our computer simulation, including the relative position of the scanner and the tree, the direction of the scanning view and scanning parameters, is set up according to the real-world arrangement of scanning. Hence, quantitative assessments of results obtained from real and simulation methods (i.e., scanned point number and depth of laser beams penetrating into the tree crown) can be compared to verify the effectiveness of the computer simulation method and provide guidance for further simulation program exploration and upgrades.

The method we propose can be applied to a variety of contexts. It is suitable for most broad-leaf trees, but our method has limited value for coniferous trees because needles are difficult to represent using triangle meshes. The scanned targets in our method can be an individual broad-leaf tree or expanded into a combination of several trees. In addition, because laser incident angles are controllable, different scanning simulations can be conducted with lateral, vertically downward and arbitrarily directional scanning. Our program can be fully extended to a range of scanning contexts. Combined with beam divergence and beam size setting, the time lapse between a laser pulse emission and its return as well as the phase shift between the emitted and received signal can also be incorporated. The simulations can therefore reproduce the performance of various laser sensors, such as Riegl (Xu et al., 2017), Leica (Sun et al., 2016), Velodyne (Atanacio-Jiménez et al., 2011) and Zebedee (Marselis et al., 2016). Our method can simulate a variety of scanning patterns, including UAV-loaded systems (Wallace et al., 2012), mobile terrestrial mapping (Xu et al., 2018) and ALS-TLS cross-scanning (Kükenbrink et al., 2017), and it can also quantify the captured leaf area and occlusion effect for different tree species with various scanning patterns.

Our scanning principle has the potential to be combined with other methods for solving many existing problems: light transmittance modelling among tree crowns with varying structural compositions in terms of leaf area density, leaf distribution and leaf angle distribution; evaluating the impact of various tree crown properties (e.g., clumping index, LAI and gap fraction) on leaf area retrieval using laser scanning techniques; and analysing the ability of intrinsic laser scanner parameters (e.g., angular resolution, beam divergence and return intensity) to characterize specific tree properties.

5. Conclusion

Using a dataset of typical trees for which the positions, sizes and directions of all leaves and branches were known we were able to construct real tree models and provide validation data to evaluate the efficacy of laser scanning techniques in estimating the total leaf area of individual trees. Designing an optimized ray intersection algorithm with adjustable parameters to simulate the laser scanning process and to obtain point clouds using various scanning patterns enables detailed data acquisition. The leaf area covered by laser beams is calculated synchronously from the scanned points using a 3D triangulation method with automatic adaptive threshold selection to provide accurate evaluations of the degree of occlusion using various scanning patterns.

The results showed that only 25–38% of leaf area was retrieved and occlusion occurred on leaves distal to the scanner when the target tree was scanned from a single terrestrial position. When three terrestrial virtual scans were performed around a tree, the accuracy of leaf area recovery reached approximately 60–72%, and occlusion was restricted to the crown centre. If a supplementary aerial virtual scan was included, leaf area recovery increased to 72–90%, depending on the leaf area index, tree crown volume and leaf area density. Our approach shows promise for tree structural measurement using laser scanning techniques in practice at the scale of individual tree leaves. With appropriate parameterization, the approach can be applied to any broadleaf tree species and any scanning patterns and can be extended to both single- and multiple-return devices. With the development of computer graphics algorithms, our approach therefore holds potential for accurate field measurements of tree leaf area.

Author contributions

Ting Yun and Lianfeng Xue wrote the programs and developed the methods; Feng An and Weizheng Li analysed the results and accuracy assessment; Bangqian Chen and Lin Cao participated in the coordination of the study and edited the manuscript; SP provided field data; MJS and MPE designed and supervised the original study; all authors contributed to the drafts of the manuscript and approved the final version for publication.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.agrformet.2019.06.009.

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