Segmenting tree crowns from terrestrial and mobile LiDAR data by exploring ecological theories

Shengli Tao^{a,b}, Fangfang Wu^a, Qinghua Guo^{a,c*}, Yongcai Wang^a, Wenkai Li^d, Baolin Xue^a,
Xueyang Hu^b, Peng Li^b, Di Tian^b, Chao Li^b, Hui Yao^b, Yumei Li^a, Guangcai Xu^a, Jingyun
Fang^b

^aState Key Laboratory of Vegetation and Environmental Change, Institute of Botany, Chinese
Academy of Sciences, Beijing 100093, China

^bDepartment of Ecology, College of Urban and Environmental Sciences, and Key Laboratory
for Earth Surface Processes of the Ministry of Education, Peking University, Beijing
100871, China

^cSierra Nevada Research Institute, School of Engineering, University of California at Merced,
Merced, CA 95343, USA

^dGuangdong Provincial Key Laboratory of Urbanization and Geo-simulation, School of
Geography and Planning, Sun Yat-sen University, Guangzhou 510275, China

* Corresponding author.

Qinghua Guo

Sierra Nevada Research Institute, School of Engineering, University of California at Merced,
CA 95343, USA

Phone: (209) 228-2911

Fax: (209) 228-4047

Email: guo.qinghua@gmail.com

Abstract – The rapid development of light detection and ranging (LiDAR) techniques is advancing ecological and forest research. During the last decade, numerous single tree segmentation techniques have been developed using airborne LiDAR data. However, accurate crown segmentation using terrestrial or mobile LiDAR data, which is an essential prerequisite for extracting branch level forest characteristics, is still challenging mainly because of the difficulties posed by tree crown intersection and irregular crown shape. In the current work, we developed a comparative shortest-path algorithm (CSP) for segmenting tree crowns scanned using terrestrial (T)-LiDAR and mobile LiDAR. The algorithm consists of two steps, namely trunk detection and subsequent crown segmentation, with the latter inspired by the well-proved metabolic ecology theory and the ecological fact that vascular plants tend to minimize the transferring distance to the root. We tested the algorithm on mobile-LiDAR-scanned roadside trees and T-LiDAR-scanned broadleaved and coniferous forests in China. Point-level quantitative assessments of the segmentation results showed that for mobile-LiDAR-scanned roadside trees, all the points were classified to their corresponding trees correctly, and for T-LiDAR-scanned broadleaved and coniferous forests, kappa coefficients ranging from 0.83 to 0.93 were obtained. We believe that our algorithm will make a contribution to solving the problem of crown segmentation in T-LiDAR scanned-forests, and might be of interest to researchers in LiDAR data processing and to forest ecologists. In addition, our research highlights the advantages of using ecological theories as guidelines for processing LiDAR data.

47 **Keywords** terrestrial LiDAR; segmentation; shortest path; mobile LiDAR; metabolic ecology

48 theory; DBSCAN

49

1. Introduction

Light detection and ranging (LiDAR) is a state-of-the-art active remote-sensing technique capable of capturing three-dimensional (3D) measurements by emitting laser light (Wehr and Lohr, 1999). In recent decades, LiDAR from different platforms, i.e., spaceborne, airborne, terrestrial, and mobile LiDAR, has shown great utility in estimating biophysical forest properties, including canopy height (Naesset 1997), forest biomass (Zhao et al., 2009; Li et al., 2015), and high-resolution carbon stock (Asner et al., 2010), because of its ability to record vertical structures on spatial scales ranging from individual trees to landscape.

Of all the LiDAR platforms available, airborne LiDAR is increasingly providing stand or tree characteristics (mean tree height, tree number, and individual tree height) over large areas (Lovell et al., 2011), but at the cost of missing details at branch level (Dassot et al., 2011). Airborne LiDAR also fails to detect small trees in lower canopy layer (Maltamo et al., 2004). As a complement to airborne LiDAR, terrestrial LiDAR (T-LiDAR) and mobile LiDAR operate underneath the canopy, and are therefore able to acquire dense point clouds recording detailed branch structures (Figure 1), for both canopy and overtopped trees in sub-canopy layers. In particular, T-LiDAR and mobile LiDAR shed new light on forest structural measurements for which traditional approaches remain time-consuming and destructive (Dassot et al., 2011). For example, the 3D structural information obtained using T-LiDAR enables tree volume metrics to be calculated by mathematical integration instead of section measurement methods (Lefsky and McHale, 2008; Dassot et al., 2012). Branch-level information including branch length, branch angle can be obtained using T-LiDAR and morphologically analyzed to explore branch networks and the structural complexity of a

forest (Moorthy et al., 2011; Bentley et al., 2013). Leaf area index, which is critical to estimate the fluxes of carbon, water, and energy between the atmosphere and trees (Zheng et al., 2013), can be accurately estimated using leaf points of individual trees scanned using T-LiDAR. Moreover, discrete points scanned using T-LiDAR and mobile LiDAR can be reconstructed into tree models, enabling computer simulation of forests, and public education through 3D visualization (Xu et al., 2007).

Figure 1. Comparison of airborne LiDAR data (A, scanned by the National Critical Zone Observatory Project) and terrestrial LiDAR (T-LiDAR) data (B). This figure shows that airborne LiDAR data can provide basic forest characteristics like tree locations and tree heights, whereas T-LiDAR data can provide detailed information at branch level such as branch angle, branch size and branch length. Accurate crown segmentation of T-LiDAR-scanned forests will therefore greatly benefit the quantification of tree branching networks. But the crown shape of trees in a forest can be extremely irregular and intersected (Figure 1B), posing great challenges for crown segmentation. Different colors in this figure indicate different height levels.

The above-mentioned forest measurements and applications require accurate crown segmentation from T-LiDAR or mobile LiDAR point cloud as an essential prerequisite (Figure 1). Recent decades have witnessed the rapid development of single-tree segmentation algorithms, but most of these are based on airborne LiDAR data. Conventionally, trees are detected from Canopy Height Models (CHMs) which are interpolated from the first return points. Hyypä et al. (2001) segmented individual trees from CHM images using a region-growing method on conifer stands. The continuing efforts of Hyypä et al. (2012) suggest that trees can be better discriminated using last-return data than using first-return data. Chen et al. (2006) used marker-controlled watershed segmentation for identifying individual trees in savanna woodlands. Popescu et al. (2002) used local filtering techniques for segmenting trees from deciduous, coniferous, and mixed stands, with the local maxima found by a round window resembling a tree crown, rather than a square one. Recently, more advanced tree detection techniques operating directly on point clouds have been developed. Reitberger et al. (2009) and Yao et al. (2012) used a normalized cut method for tree segmentation from waveform LiDAR data. Li et al. (2012) developed a top-down region-growing point cloud segmentation (PCS) method for segmenting complex mixed forests. PCS obtained an overall accuracy of 94% in the Sierra National Forest, which was overwhelmingly superior to the traditional marker-controlled watershed segmentation (Tao et al., 2014).

Accurate individual tree crown segmentation using T-LiDAR or mobile LiDAR data is still challenging, especially for broadleaved trees of which tree crowns can be extremely

irregular and are often heavily intersected (Figure 1B). Although there have been pioneering studies on tree segmentation using T-LiDAR data or mobile LiDAR data, the focus tends to be trunk detection (Simonse et al., 2003; Gorte and Pfeifer, 2004; Brolly and Kiraly, 2009; Huang et al., 2011; Schilling et al., 2011; Olofsson et al., 2014), and tree crowns are often simply approximated as a cylinder centralizing tree trunks or tree tops. For examples, Bienert et al. (2006) and Maas et al. (2008) automatically detected trunks from T-LiDAR point clouds, and further approximated the crown part of a tree as a vertical cylinder with a predefined radius surrounding the stem. Similarly, Livny et al. (2010) segmented roadside trees by classifying points within a constant distance around local maxima into a single tree point cluster. Wu et al. (2013a) segmented roadside trees with high accuracy using a voxel-based marked-neighborhood-searching method. However, roadside trees are uniform in crown shape and usually not crown intersected, therefore previous methods for segmenting roadside trees might not be able to deal with forests exhibiting crown intersecting and irregular crown shapes.

This paper proposes a new algorithm for segmenting individual tree trunks as well as crowns from both mobile-LiDAR-scanned roadside trees and T-LiDAR-scanned forest (including both broadleaved and coniferous forests). The newly proposed algorithm, namely the comparative shortest-path algorithm (CSP), was inspired by ecological basis and classical metabolic ecological theory (Leopold, 1971; West et al., 1999a). The development of the new algorithm is a basis for our future researches aiming at quantifying the branching network of trees. To give a clear illustration of the new algorithm, the rest of this paper is organized as follows: the datasets for testing the algorithm are specified in Section 2, followed by a

detailed illustration of the algorithm in Section 3. To demonstrate the effectiveness of the comparative shortest-path algorithm, the PCS algorithm developed by Li et al. (2012) was performed on the same dataset and the results were compared with those obtained using the new algorithm. Sections 4 and 5 provide a comparison of the results and evaluate the two algorithms. Finally, conclusions are drawn in Section 6.

2. Datasets

Five datasets were used for testing our algorithm, including four T-LiDAR-scanned forest plots in China (Figure 2), and one mobile-LiDAR-scanned point cloud of roadside trees. In February 2014, during the leaf-off period, a *Carya illinoensis* forest plot (Plot 1 hereafter) in the Beijing Botanical Garden was scanned using a Riegl VZ400 (Riegl Inc., Austria) T-LiDAR system mounted on a tripod (Table 1). In September 2014, during the leaf-on period, the plot was scanned a second time. In addition, a *Pinus tabuliformis* forest plot (Plot 2 hereafter) in Dongling Mountain in Beijing and a *Castanopsis Sclerophylla* forest plot (Plot 3 hereafter) in Anhui province in China were scanned using the same T-LiDAR system in December 2014 and January 2015, respectively (Figure 2). The sampling setup was distributed on a 10 m × 10 m grid in each plot (Cifuentes et al., 2014). To ensure point density at the crown part, additional scanning towards forest canopy was also conducted. Plot 1 consists of trees of different sizes and irregular crown shapes (Figure 1B; Table 2). Small trees in this plot are overtopped by large trees, posing challenges for crown segmentation. Plot 2 is planted forest with a constant planting distance of ca. 1.6 m, and is therefore heavily crown intersected. Plot 3 is a natural forest with not only intersecting canopy observed, but also

higher shrub coverage under canopy layer, which causes difficulty for both trunk detection and crown segmentation. The point cloud for each plot was integrated from separate scanning, and finally downsampled to keep an averaged point distance of 10 cm to reduce computational burden using RISCAN PRO software (Riegl Inc., Austria).

Figure 2. Forest plots scanned using Riegl VZ 400 T-LiDAR system and their point clouds for testing the proposed new algorithm. The testing forest data includes *Carya illinoensis* forest during both leaf-off and leaf-on conditions in the Beijing Botanical Garden (top), *Pinus tabulaeformis* forest in Dongling Mountain in Beijing (middle), and *Castanopsis Sclerophylla* forest in Jitan, Anhui Province, China (bottom).

Table 1. Specification of Riegl VZ-400 terrestrial LiDAR system and Li-mobile LiDAR system.

Riegl VZ-400	Field of view	Horizontal: 0–360° Vertical: –40° to 60°
	Effective measurement rate	Up to 122,000 measurements/s
	Detection range	600 m at 90% reflectivity
	Laser beam divergence	0.35 mrad
	Scanning accuracy	2 mm at 100 m distance
	Minimum range	1.5 m
	Laser wavelength	Near infrared
	Camera	Equipped with Nikon D300s
	Scanner weight	9.8 kg
Li-mobile	Detection range	Up to 70 m
	Scanning accuracy	2 cm
	Vehicle velocity	20–60 km/h
	Scanning mode	Fixed direction
	Vertical scanning angle	360°
	Points per second	Up to 700,000
	Scanner weight	1 kg

178 Table 2. Forest plots scanned using Riegl VZ400 T-LiDAR system for testing the proposed algorithm. The numbers inside parentheses are the
 179 number of scans conducted toward forest canopy.

	Size (m ²)	Leaf form	Dominant species	Slope(degree)	Number of trees	Min/max DBH(cm)	Number of scans	Scan date
Plot 1							16 (8)	February, 2014
	10*10	Broadleaved	<i>Carya illinoensis</i>	2	14	5.2/42.6	16 (8)	September, 2014
Plot 2	15*10	Coniferous	<i>Pinus tabuliformis</i>	33.3	51	3.0/32.2	18 (9)	December, 2014
Plot 3	15*10	Broadleaved	<i>Castanopsis</i> <i>Sclerophylla</i>	25.5	49	13.5/23.4	16 (8)	January, 2015

The roadside trees were scanned using a Li-mobile LiDAR system (LiForest Ltd., Co.) at the Beijing Botanical Garden (Table 1). The mobile LiDAR system consisted of three major components: a Velodyne laser scanner, NovAtel Inertial Measurement Unit (IMU), and NovAtel high-precision Global Positioning System (GPS). The scanning angles of the laser scanner spanned a range up to 360° and the angle resolution was 0.1°. The IMU measured and reported the vehicle's velocity, orientation, and gravitational forces. Together with the time information provided by the GPS, point clouds were generated automatically. The density of the point cloud depended on both the scanning speed of the laser scanner, which was up to 700,000, and the velocity of the vehicle, which was around 25 km/h in our case, resulting in clear recording of trees.

3. Methodology

3.1 Comparative shortest-path algorithm (CSP)

The strategy for individual tree segmentation consisted of three major parts: point cloud normalization, trunk detection and DBH estimation, and finally crown segmentation. In addition, we also performed PCS developed by Li et al. (2012) and compared the results with those obtained using the comparative shortest-path algorithm.

Step 1: Point cloud normalization

The point clouds were normalized before segmentation using the following formula:

$$Z_i - Z_i^{\text{dem}} \quad (1)$$

where Z_i is the z -value of the i th point, and Z_i^{dem} is the corresponding value of the Digital Elevation Model (DEM) grid onto which the point is projected. The DEM was interpolated using ordinary kriging method at 0.2 m resolution (Guo et al., 2010), with the lowest points in each 0.25 m² grid treated as ground points (McDaniel et al. 2012). After normalization, the elevation value of each point indicates the height from zero (ground) to the point (Li et al., 2012). It is worth mentioning that point cloud normalization does not change the spatial distribution of trees and branches.

Step 2: Trunk detection and DBH estimation

In contrast to forest canopy, which tends to intersect as a result of competition for light, trunks are naturally separated from each other and can therefore be accurately detected. In the current research, a cluster algorithm, namely Density-based spatial clustering of applications with noise (DBSCAN), was adopted for trunk segmentation, because it has the merits of robustness to noise points and efficiency (Wu et al., 2013b). DBSCAN is a density-based clustering algorithm that does not require the number of clusters as an input parameter (as opposed to the k-means algorithm). Instead, by defining the minimum number of points required to form a cluster (MinPts) or the radius of the neighborhood (Eps-neighborhood of a point), DBSCAN is able to detect clusters of arbitrary shape automatically. Starting with any arbitrary point p in point cloud D , the Eps-neighborhood of p , denoted by $N_{\text{Eps}}(p)$, is defined as the set of points q (including point p itself) such that the distance between p and q is within Eps:

$$N_{\text{Eps}}(p) = \{q \in D \mid \text{dist}(p, q) \leq \text{Eps}\} \quad (2)$$

If there are enough points contained in that neighborhood, which means $|N_{Eps}(q)| \geq \text{MinPts}$, a cluster is initiated; otherwise, p is labeled as a noise point (Ester et al., 1996; Wu et al., 2013b). This procedure is repeated for each point that has not been visited. It is worth noting that the two parameters required for DBSCAN, namely MinPts and Eps, need not to be provided at the same time. Eps can be calculated from the size of the point cloud and MinPts when the points exhibit a relatively uniform distribution, using the following equations (Daszykowski et al., 2002):

$$Eps = \sqrt{\frac{T \cdot \text{MinPts} \cdot \Gamma[(1/2) \cdot n + 1]}{m \sqrt{\pi^n}}} \quad (3)$$

$$T = \prod_{i=1}^n \{\max(X_i) - \min(X_i)\} \quad (4)$$

where m denotes the number of points, n is the dimensionality of the points, Γ is the gamma function, X is the point dataset, and T is the volume of the experimental space formed by m points.

DBSCAN is well suited to automatic trunk segmentation because the number of trunks in a plot is not available in advance. To apply DBSCAN to our plot, a point slice of vertical size of 10 cm cut from the point cloud at a height of 1.3 m was used as the input, and the parameter MinPts was set at 2. Figure 3A shows the trunks detected using DBSCAN, taking the T-LiDAR-scanned deciduous forest plot (Plot 1) as an example. After trunk segmentation, the size of each trunk was quantified and the DBH was measured from the points as follows: first, for each trunk slice, the gravity centers of all the points were calculated, and then radius was calculated as the mean distance from the weight center to the points forming the trunks (Haralick, 1974); finally, DBH was calculated from radius. If a point slice from 1.3 m was not

available due to shrub occlusion, point slices below 1.3 m were used for DBH measurement. The estimated DBH values from LiDAR points were highly correlated with ground-truth measurements, indicating the effectiveness of the DBH-extraction method (Figure 3B).

Figure 3. Trunk detection using DBSCAN (A) and accuracy of DBH estimation (B); T-LiDAR-scanned broadleaved forest is used as an example. Trunks are indicated in different colors.

Step 3: Crown segmentation

The branch vascular structure of a tree is filled with conducting tubes for transferring water and other nutrients, therefore “paths” can be imaged inside the vascular structure stretching continuously from the roots to the leaves through the trunk, second-order branches, lower-order branches, twigs, and petioles, successively. For trees that are space-sparsely distributed with no crown intersection, the paths originating from the trunk of one tree to any part of its crown do not reach other trees, because no route bridging the target trees to its neighbors is available (Figure 4A). The points in the paths originating from the trunk of the

target tree therefore all belong to the target tree. In contrast, for trees of which the crowns connect and intersect, paths will run continuously into neighboring trees intersecting with the target tree at the crown part. This poses a great challenge for crown segmentation. Fortunately, for the purpose of maximizing efficiency, the structural designs of trees have been shaped by evolution in a way that reduces the distances over which materials are transported (Leopold 1971; West et al., 1999a). Thus, according to this biological theory, if two trees of equal size are crown intersected, the points at the intersecting part probably belong to the tree to the trunk of which a shorter transporting distance can be obtained (Figure 4B). For crown-intersecting trees that differ greatly in size, a direct comparison between transporting distances is not appropriate, as shown in Figure 4C, in which points v_1 and v_2 belong to Tree₁, but the distances from v_1 and v_2 to Trunk₁ are longer than the distances to Trunk₂. As a consequence, part of Tree₁ will be falsely segmented to Tree₂. In order to deal with this problem, we can scale the transporting distance before comparison, using the metabolic ecology theory (West et al., 1999b; Enquist, 2002; Bentley et al., 2013), which suggests the existence of a universal power-law relationship between branch length and branch radius, with a fixed scaling exponent close to 2/3. In other words, the transporting distances of one tree were scaled using the following equation, before comparing the transporting distances:

$$D_{v \rightarrow \text{Trunk}}^N = D_{v \rightarrow \text{Trunk}} / \text{DBH}^{2/3} \quad (5)$$

where $D_{v \rightarrow \text{Trunk}}$ is the transporting distance from point v to the tree trunk and $D_{v \rightarrow \text{Trunk}}^N$ is the DBH-scaled transporting distance. Note that DBH of each trunk was calculated in step 2.

Figure 4. Conceptual images illustrating the comparative shortest-path algorithm (CSP), taking two trees as an example. (A) Two trees are not crown intersected, and point v (together with other points in Tree₁) will be classified to Tree₁, because path (indicated by the red line) is only available to the root of Tree₁; (B) two trees of equal size are crown intersected, and point v (together with other points in Tree₁) will still be classified to Tree₁ because path distance to the root of Tree₁ is shorter than that to the root of Tree₂; (C) two trees of different size are crown intersected, and points v_1 and v_2 of Tree₁ will be falsely classified to Tree₂ if the rule in Figure 4B is directly applied; to reduce errors, we therefore scaled the path distances according to metabolic ecology theory before comparison of path distances.

In summary, if we can identify and calculate the path from the T-LiDAR point cloud resembling the conducting path through which nutrients and water are conducted, points can be classified into individual trees using the above-mentioned strategy, which is named as comparative shortest-path strategy. Fortunately, the path and transporting distance can be obtained using the shortest-path algorithm of graph theory, which has been extensively used by previous researchers for tree topology analysis (Xu et al., 2007; Livny et al., 2010; Schilling et al., 2012). In short, the whole procedure can be summarized in the following steps:

- 1) establish a graph $G = (V, E)$ from the LiDAR point cloud of trees, where V represents the vertices (points of point cloud) and E represents the edges (connection between two points);
- 2) calculate the shortest paths and DBH-scaled shortest paths using Dijkstra's shortest-path algorithm (Dijkstra, 1959); and
- 3) classify the points using the comparative shortest-path strategy.

1) To establish the graph G , LiDAR points were organized using a kd-tree structure, to speed up the process. Then a range search was conducted to connect each point v with its neighbors within a fixed 3D Euclidean distance.

2) Given a graph $G = (V, E)$, with weight function $w: E \rightarrow \mathbf{R}$ mapping edges to Euclidean distance weights (Cormen et al., 2009), and a path p as a sequence of vertices $p = (v_1, v_2, \dots, v_k)$, such that each adjacent pair of vertices is connected by an edge, the weight of path p denoted as $w(p)$ is defined as sum of the weights of its constituent edges:

$$w(p) = \sum_{i=1}^k w(v_{i-1}, v_i) \quad (6)$$

The shortest-path problem can then be expressed as follows: starting from the source vertex u , find the path to vertex v under the constraint of minimizing the weight of the constituent

edges $w(u,v)$ of path p . If there is no path stretching from vertex u to vertex v , the weight of this shortest path is treated as infinite. In summary, the shortest-path weight $w(p)$ is

$$w(p) = w(u,v) = \begin{cases} \min\{w(p): u \xrightarrow{p} v\} & \text{if there is a path from } u \text{ to } v \\ \infty & \text{otherwise} \end{cases} \quad (7)$$

3) For trees that are space-sparsely distributed with no crown intersection as in the case of mobile-LiDAR-scanned roadside trees, points were classified as follows: let $Tree_1$ be the target tree, the trunk of $Tree_1$ be denoted by $Trunk_1$, and let $D_{v \rightarrow Trunk_1}^N$ symbolize the DBH-scaled shortest-path distance from point v to $Trunk_1$ (Figure 4A):

for each point $v \in V$:
 if $D_{v \rightarrow Trunk_1}^N \neq \infty$
 $v \in Tree_1$

For trees with crowns that are heavily intersected, the above-mentioned comparative shortest-path strategy is used to classify the points in the crown-intersecting area (Figures 4B and 4C): if $Tree_1$ and $Tree_2$ are crown intersected, for point $v \in Tree_1$ and $Tree_2$, we classify v using the following rules:

if $D_{v \rightarrow Trunk_1}^N < D_{v \rightarrow Trunk_2}^N$:
 $v \in Tree_1$
 else
 $v \in Tree_2$

where $D_{v \rightarrow Trunk_1}^N$ symbolizes the scaled shortest-path distance from point v to the trunk of $Tree_1$ and $D_{v \rightarrow Trunk_2}^N$ symbolizes the scaled shortest-path distance from point v to the trunk of $Tree_2$.

For clarity, we have presented examples containing only two trees to illustrate the comparative shortest-path algorithm. To segment all the points into corresponding trees simultaneously, the following pseudo codes can be used:

for each point $v \in V$:
 Calculate D_v^N to each neighboring trunk

$v \in \text{Tree}$ to the trunk of which the shortest D^N_v was obtained

3.2 Point cloud segmentation

The PCS algorithm developed by Li et al. (2012) was compared with the comparative shortest-path algorithm. The core idea of the PCS is summarized as follows: treating the highest point in a point cluster as a tree top, each point below the tree top is judged using a spacing threshold rule to determine whether the point belongs to the tree initialized by the tree top. A single tree is segmented out after all points below the highest point have been judged, and this procedure is implemented iteratively for other trees, as shown in the following pseudo code:

```
While  $P$  is not empty:
    if point  $a$  is a local maximum in two-dimensional circular space with a radius  $R$ :
        if  $dmin1 > d$ : point  $a$  belongs to  $Ni$ ;
        if  $dmin1 \leq d$  and  $dmin1 < dmin2$ : point  $a$  belongs to  $Ti$ ;
        if  $dmin1 \leq d$  and  $dmin1 > dmin2$ : point  $a$  belongs to  $Ni$ ;
    else:
        if  $dmin1 \leq dmin2$ : points  $a$  belongs to  $Ti$ ;
        if  $dmin1 > dmin2$ : point  $a$  belongs to  $Ni$ ;
     $P = P - Ti$ ;
```

where P denotes the point cloud, Ti denotes the target tree that will be segmented at the i th time, Ni is an outlier set, $dmin1$ (or $dmin2$) denotes the minimum two-dimensional (2D) Euclidean distance from any point in Ti (or Ni) to point a , and d is an adaptive spacing threshold (Li et al., 2012; Tao et al., 2014).

3.3 Implementation

We used Matlab 2013b with the parameter Eps set at 2 for the DBSCAN procedure, to detect individual trunks from both T-LiDAR-scanned forest and mobile-LiDAR-scanned roadside trees. Each trunk (with its DBH) is assigned a unique ID. The shortest-path algorithm for

crown segmentation was then implemented in C++ using the boost graph library with a fixed neighbor search radius of 30 cm for all the testing point clouds (Siek et al., 2001). Point classified to a trunk will be labeled with the same ID with its belonging trunk. The entire procedure can thus be imaged as growing each trunk into a tree by finding the points closer to it than to neighboring trunks in terms of shortest-path distance. For mobile-LiDAR-scanned roadside trees, the shortest paths were not scaled, in order to reduce the computational burden.

We then used LiForest (<http://www.liforest.com>) software to implement the PCS algorithm. The horizontal threshold for the PCS was set at 1.0 m for Plot 1 and 0.5m for Plots 2 and 3, based on trial and error. The point clouds for broadleaved trees (i.e., Plot 1 and Plot 3) were inverted (i.e., rotated 180 degrees) before the implementation of PCS to achieve better segmentation accuracy.

3.4 Accuracy assessment

We assessed the segmentation results at not only tree level, but also point level. For tree level assessment, if a tree exists and is segmented out from the point cloud, it is called true positive (TP); if a tree is not segmented but assigned to a nearby tree, it is called false negative (FN); if a tree does not exist but is segmented from the point cloud, it is called false positive (FP). High TP value and low FN and FP values correspond to high accuracy. To evaluate the accuracy at tree level, we calculated recall (r), precision (p), and F -score using the following equations (Goutte and Gaussier 2005; Sokolova et al., 2006):

$$F = 2 \times \frac{r \times p}{r + p} \quad (8)$$

$$\text{where } r = \frac{TP}{TP + FN} \text{ and } p = \frac{TP}{TP + FP} \quad (9)$$

For point level assessment, the ground truth points for each tree were first extracted from point clouds manually under careful visual inspection using ArcScene 10.1(ESRI Inc.). Then for each segmented tree, true positive points, false positive points (points belongs to other trees) and false negative points (points segmented to other trees) were identified and organized into an error matrix. We finally calculated r , p , F -score, false rate (i.e., ratio of falsely segmented points) and Cohen's kappa coefficient based on the error matrix to assess the segmentation accuracy at point level.

4. Results

Figure 5 shows the segmentation results for mobile-LiDAR-scanned roadside trees obtained using the comparative shortest-path algorithm (Figure 5A) and PCS (Figure 5B). Visual inspection indicates that both the algorithms succeed in segmenting roadside trees exhibiting no crown intersections, with no false segmentation observed. Figure 6 and supplementary video show the segmentation results for the T-LiDAR-scanned forest plots, obtained using the comparative shortest-path algorithm (A-D) and PCS (E-H); the accuracy assessments of the segmentation results at tree level are shown in Table 3. Individual trees in Plot 1(both leaf-off and leaf-on conditions) and Plot 2 were correctly segmented from the point cloud by the comparative shortest-path algorithm, but for Plot 3, four trees were falsely segmented because of trunk occlusion (Table 3; Figure 6; supplementary video). In contrast, much more trees were falsely segmented by PCS, including four false-positive and four false negative trees for Plot 1, 15 false-positive and 12 false negative trees for Plot 2, and one false-positive and 13 false negative trees for Plot 3 (Table 3; Figure 6; supplementary video).

409

410

411 Figure 5. Segmentation results for mobile LiDAR scanned roadside trees using comparative
412 shortest-path algorithm (A) and PCS algorithm (B). This figure indicates that both algorithms
413 are able to segment trees that are not crown intersected. Different colors indicate different
414 trees.

415

416 Figure 6. Trees segmented using the comparative shortest-path algorithm for Plot 1 during leaf-off condition (A), Plot 1 during leaf-on condition

417 (B), Plot 2 (C) and Plot 3 (D). E-H are the same plots segmented using PCS algorithm. Different colors indicate different trees. For quantitative

418 assessments on the segmentation results, see Table 3 and Figure 7. Please also see supplementary video for more details on the segmentation

419 results.

420 Table 3. Accuracy assessments of segmentation results at tree level. CSP stands for the comparative shortest-path algorithm and PCS stands for
 421 the point cloud segmentation algorithm. For point-level assessments, see Figure 7.

	Number of trees	Number of segmented trees	TP	FP	FN	r	p	F
Plot 1 by CSP (leaf off)	14	14	14	0	0	1	1	1
Plot 1 by PCS (leaf off)	14	14	10	4	4	0.71	0.71	0.71
Plot 1 by CSP (leaf on)	14	14	14	0	0	1	1	1
Plot 1 by PCS (leaf on)	14	14	10	4	4	0.71	0.71	0.71
Plot 2 by CSP	51	51	51	0	0	1	1	1
Plot 2 by PCS	51	54	39	15	12	0.76	0.72	0.74
Plot 3 by CSP	49	44	44	0	4	0.92	1	0.96
Plot 3 by PCS	49	37	36	1	13	0.73	0.97	0.84

The accuracy assessments at the point level suggest that the overall accuracy of the comparative shortest-path algorithm is high in terms of r score, p score, F score and kappa coefficients. The kappa coefficients for the comparative shortest-path algorithm ranged from 0.83 to 0.93, with the lowest value of 0.83 obtained in plot 3 and highest value of 0.93 in Plot 2 (Figure 7). The false rates ranged from 5% to 16% (Figure 7), and most falsely segmented points were located at the outer-most parts of the crowns (Figure 6). Compared with the high accuracy obtained using the comparative shortest-path algorithm, the results obtained using PCS showed low accuracy, with kappa coefficients ranging from 0.30 to 0.65 and false rate ranging from 33% to 64% (Figure 7). Despite the overall low accuracy, the segmentation results by PCS for coniferous forest (i.e., Plot 3) were much better than broadleaved forest (i.e., Plot 1 and Plot 3) (Figure 7). Totally 6.1% points and 33.9% points were falsely segmented during leaf-off condition by the comparative shortest-path algorithm and PCS, respectively, whereas the falsely segmented points represented 13.2% and 53.5%, respectively, during leaf-on condition (Figure 7). In summary, the segmentation results at both tree level and point level demonstrate the superiority of the comparative shortest-path algorithm over PCS.

Figure 7. Point level accuracy assessments for Plot 1 during leaf-off condition (A), Plot 1 during leaf-on condition (B), Plot 2 (C) and Plot 3 (D). CSP stands for the comparative shortest-path algorithm and PCS stands for the point cloud segmentation algorithm.

5. Discussion

5.1 Comparison of segmentation results obtained using comparative shortest-path algorithm and PCS

Both the comparative shortest-path algorithm and PCS produce high accuracy with respect to segmenting mobile-LiDAR-scanned roadside trees (Figure 5). Figure 4A clearly shows the ability of the comparative shortest-path algorithm to segment roadside trees. PCS is also expected to be successful because PCS seeks local maxima as seed points, and then grows the point cluster by judging a predefined horizontal spacing threshold. As long as the tree top is clearly presented and the spacing threshold is appropriately defined, PCS is able to segment

individual trees accurately. In this study, the roadside trees were “naturally” separated from each other in space, which makes it easy to select the spacing threshold for PCS. Several methods have been proposed for segmenting roadside trees (Livny et al., 2010; Wu et al., 2013a). Previous research, together with the successes of the comparative shortest-path algorithm and PCS, lays a solid foundation for tree characteristic extraction using T-LiDAR and mobile LiDAR.

For T-LiDAR-scanned trees in forests with crown intersections, the comparative shortest-path algorithm shows high accuracy, even at the point level, and outperforms PCS (Figures 6 and 7). The segmentation results using the comparative shortest-path algorithm for Plot 1 and Plot 2 are better than that for Plot 3, because four trunks were not scanned in Plot 3 as a result of occlusion. The segmentation result for Plot 2 (coniferous) is better than that of Plot 1 and Plot 2 (both broadleaved) using PCS. PCS is originally designed to process airborne LiDAR data in coniferous forests; it is based on a 2D horizontal spacing threshold which cannot cope with horizontal crown-intersecting issues (Tao et al., 2014). As shown in Figure 6, a large number of shoots were misclassified by PCS, because of the irregular shapes of the tree crowns and the heavy intersection. In contrast, the comparative shortest-path algorithm is a bottom-up region-growing approach designed to process T-LiDAR data; it classifies points one by one using the 3D path distance to the tree trunk instead of a constant 2D spacing threshold to the tree set. The path distance is biologically meaningful, which helps to allocate points at the intersecting region to the corresponding trees (Figure 8). The superiority of CSP over PCS is therefore confirmed for ground-based LiDAR and for segmenting broadleaved forest in this study.

Figure 8. Details of the segmentation results for trees in Figure 1B, part of Plot 1. This figure shows the comparative shortest-path algorithm is able to segment crowns with irregular shapes.

5.2 Comparison of segmentation results obtained during leaf-off and leaf-on conditions

The kappa coefficient for the comparative shortest-path algorithm during leaf-off condition is 0.92, slightly higher than that of 0.84 during leaf-on condition. Similarly, the kappa coefficient for PCS during leaf-off condition is 0.46, also higher than that of 0.30 during leaf-on condition. Meanwhile, the false rate for the leaf-off condition is much lower than that for leaf-on condition (Figure 7). According to the results obtained using both the comparative shortest-path algorithm and PCS, the accuracy for leaf-off condition is higher than that for leaf-on condition (Figure 7). Leaves greatly increase the point quantity and complicate crown intersecting, making individual tree segmentation of the crown part more difficult, as

demonstrated by the results: the falsely segmented points amount to 6.1% for comparative shortest-path algorithm and 33.9% for PCS during leaf-off condition, whereas increased to 13.2% and 53.5%, respectively, during leaf-on condition. For the comparative shortest-path algorithm, this phenomenon can be explained by the fact that the leaf clusters shade twigs and small branches, and this influences the correct extraction of the shortest path for some crown points.

5.3 Parameters of comparative shortest-path algorithm

Two parameters are optimized by the comparative shortest-path algorithm: MinPts for DBSCAN and the search radius for building a graph among the cloud points. However, neither of these two parameters is sensitive to testing datasets and, furthermore, they can be set at fixed values provided same sampling setup. The first parameter, MinPts, of DBSCAN for detecting trunks, is determined directly from the point density. For a given T-LiDAR sampling setup, the point density at each trunk slice should be highly uniform (Cifuentes et al., 2014). In addition, the distance between trunks is much greater than the average distance among LiDAR points; this also ensures the success of DBSCAN, because trunks “naturally” fall into separate clusters. The second parameter is the search radius for building a graph of LiDAR-scanned points. This parameter is also directly determined by the LiDAR point density. It is worth mentioning that DBSCAN was chosen for trunk segmentation not only because of its accuracy, but also its ability to exclude noise points which might represent shrubs. DBSCAN labels all points as core, border, or noise points: Given a point p , if the size of $N_{Eps}(p)$ is at least MinPts, then p is a core point; if it is not a core point but $N_{Eps}(p)$ contains at least one core point, p is a border point; otherwise, p is treated as a noise point. In our case,

shrub point slice at 1.3 m height is low in point density and were classified as noise points by DBSCAN. However, we acknowledge that if the input point slice for DBSCAN contains shrub points which meet the standard of “core” or “border” points, DBSCAN is not able to eliminate them. Thus, for a forest with complex under-canopy conditions, DBSCAN can be replaced with circle-fitting procedures to identify circles directly from point slice (Tao et al., 2015). Our algorithm is being integrated into LiForest software (<http://www.liforest.com>) and circle-fitting procedures will be available to exclude shrubs.

The comparative shortest-path algorithm requires the branch structure at the crown part to be adequately scanned using T-LiDAR or mobile LiDAR, for calculating the correct shortest paths for points at tree crowns. Otherwise, the distance of the shortest path from insufficiently scanned branches might be falsely calculated, and the points at the corresponding sections will be falsely classified. In Plot 3, four trees were falsely segmented because of trunk occlusion (Table 3; Figure 6). This indicates that gaps within point clouds can influence the segmentation accuracy of the comparative shortest-path algorithm. Meanwhile, the method for DBH calculation might be biased towards underestimation at scanning from one direction (Figure 3B). To maximize the expected utility of the comparative shortest-path algorithm, we therefore recommend multi-scanning when field scanning is conducted. Meanwhile, a searching probe for connecting the disconnected graph components will be integrated into the proposed algorithm (Xu et al., 2007), to make it robust to occlusions. For forest plots in which tree sizes are uniform, the normalization of conducting paths can also be omitted to reduce computational burden.

5.4 Ecological theories as guidelines to process LiDAR data

The comparative shortest-path algorithm fully takes advantage of ecological basis and metabolic ecology theory as guidelines (Leopold, 1971; West et al., 1999a). Metabolic ecology theory is a universal scaling law of tree growth and has strong empirical support (Enquist, 2002; Bentley et al., 2013). This ensures that the proposed new algorithm might be extensively applicable. Although there will always be trees deviating from the scaling exponents of $2/3$, our segmentation results demonstrate that metabolic ecology theory can be applied to segmenting broadleaved and coniferous forests (Figure 6 and supplementary video), and relatively high accuracies can be achieved. It's been suggested that the use of metabolic scaling theory should take factors like demographic traits and light into consideration (West et al., 1999b; Bentley et al., 2013), and our future work will continue to explore these issues. In fact, the effectiveness of metabolic ecology theory in assisting LiDAR data processing has also been reported by previous researchers: Chen et al. (2007) estimated individual-tree basal areas and stem volumes based on a recent advance in the metabolic ecology theory by Enquist (2002). The results obtained by Chen et al. (2007) suggest that models built based on allometry theory are the best in terms of accuracy and sensitivity to errors in tree crown segmentation. Swetnam and Falk (2014) developed a variable-area local maxima algorithm that incorporates the predictions of ecological metabolic scaling theory into segmentation of individual trees, and found that the frequency of commission errors was greatly reduced. These studies together with our segmentation algorithm suggest that the use of ecological theories as guidelines for processing LiDAR data might improve the accuracy as well as the efficiency.

6. Conclusion

Forest scanned using T-LiDAR or mobile LiDAR are difficult to segment in terms of crown segmentation. In this study, we developed a comparative shortest-path algorithm (CSP) with the aim of segmenting both broadleaved and coniferous forests scanned using T-LiDAR and roadside trees scanned using mobile LiDAR. The proposed algorithm shows high accuracy not only in terms of the number of tree detected but also in terms of crown segmentation. Visual inspection of the segmentation results suggested that high accuracy can be obtained, with tree trunks successfully segmented from the point cloud but not missing details at the crown parts. Furthermore, kappa coefficients at point levels ranging from 0.83 to 0.93 were obtained for different testing dataset. A comparison with the PCS method reported by [Li et al. \(2012\)](#) further demonstrated the superiority of CSP in segmenting broadleaved trees scanned using T-LiDAR. The success of the proposed new algorithm provides a solid foundation for our future research, where accurately segmented tree crowns will be analyzed to obtain branch and leaf level forest characteristics, and finally quantify the branching network of trees.

Acknowledgments

We thank Wenhan Cao for preparing Figure 4, and Shuxin Pang, Linhai Chen, Yongyi Zhu and Xin Yu for their assistance in LiDAR scanning. We also thank the reviewers for their constructive comments and recommendations. This work was partly supported by the National Natural Science Foundation of China (#31321061, 31330012, 41471363 and 41401505).

577 **References**

- 578 Asner, G.P., Powell, G.V.N., Mascaro, J., Knapp, D.E., Clark, J.K., Jacobson, J.,
579 Kennedy-Bowdoin, T., Balaji, A., Paez-Acosta, G., Victoria, E., Secada, L., Valqui, M.,
580 Hughes, R.F., 2010. High-resolution forest carbon stocks and emissions in the Amazon.
581 Proc Natl Acad Sci USA 107(28), 16738–16742.
- 582 Bentley, L.P., Stegen, J.C., Savage, V.M., Smith, D.D., von Allmen, E.I., Sperry, J.S., Reich,
583 P.B., Enquist, B.J., 2013. An empirical assessment of tree branching networks and
584 implications for plant allometric scaling models. Ecol Lett 16(8), 1069–1078.
- 585 Bienert, A., Scheller, S., Keane, E., Mullooly, G., Mohan, F., 2006. Application of terrestrial
586 laser scanners for the determination of forest inventory parameters. Int Arch
587 Photogramm Remote Sens Spatial Inf Sci 36 (Part 5).
- 588 Brolly, G., Kiraly, G., 2009. Algorithms for stem mapping by means of terrestrial laser
589 scanning. Acta Silvatica et Lignaria Hungarica 5, 119–130.
- 590 Chen, Q., Baldocchi, D., Gong, P., Kelly, M., 2006. Isolating individual trees in a savanna
591 woodland using small footprint LiDAR data. Photogramm Eng Rem S 72(8), 923–932.
- 592 Chen, Q., Gong, P., Baldocchi, D., Tian, Y.Q., 2007. Estimating basal area and stem volume
593 for individual trees from LiDAR data. Photogramm Eng Rem S 73(12), 1355–1365.
- 594 Cifuentes, R., Van der Zande, D., Farifteh, J., Salas, C., Coppin, P., 2014. Effects of voxel
595 size and sampling setup on the estimation of forest canopy gap fraction from terrestrial
596 laser scanning data. Agr Forest Meteorol 194, 230–240.
- 597 Cormen, T. H., Leiserson, C. E., Rivest, R. L., Stein, C., 2009. Introduction to algorithms,
598 third ed. Vol. 6, pp. 643. Cambridge: MIT press.

599 Dassot, M., Colin, A., Santenoise, P., Fournier, M., Constant, T., 2012. Terrestrial laser
 600 scanning for measuring the solid wood volume, including branches, of adult standing
 601 trees in the forest environment. *Comput Electron Agr* 89, 86–93.

602 Dassot, M., Constant, T., Fournier, M., 2011. The use of terrestrial LiDAR technology in
 603 forest science: application fields, benefits and challenges. *Ann For Sci* 68(5), 959–974.

604 Daszykowski, M., Walczak, B., Massart, D.L., 2002. Looking for natural patterns in
 605 analytical data. 2. Tracing local density with OPTICS. *J Chem Inf Comp Sci* 42(3),
 606 500–507.

607 Dijkstra, E.W., 1959. A note on two problems in connexion with graphs. *Numer Math* 1,
 608 269–271.

609 Ester, M., Kriegel, H. P., Sander, J., Xu, X., 1996. A density-based algorithm for discovering
 610 clusters in large spatial databases with noise, August. In *Kdd*, Vol. 96, pp. 226–231.

611 Enquist, B.J., 2002. Universal scaling in tree and vascular plant allometry: Toward a general
 612 quantitative theory linking plant form and function from cells to ecosystems. *Tree*
 613 *Physiol* 22(15-16), 1045–1064.

614 Gorte, B., Pfeifer, N., 2004. Structuring laser-scanned trees using 3D mathematical
 615 morphology. *International Archives of Photogrammetry and Remote Sensing* 35,
 616 929-933.

617 Goutte, C., Gaussier, E., 2005. A probabilistic interpretation of precision, recall and F-score,
 618 with implication for evaluation. *Lect Notes Comput Sc* 3408, 345-359.

619 Guo, Q.H., Li, W.K., Yu, H., Alvarez, O., 2010. Effects of topographic variability and
620 LiDAR sampling density on several DEM interpolation methods. *Photogramm Eng Rem*
621 *S* 76(6), 701–712.

622 Haralick, R.M., 1974. A measure of circularity of digital figures. *IEEE Trans. Systems Man*
623 *Cybernet.* 4(4), 394–396.

624 Huang, H.B., Li, Z., Gong, P., Cheng, X.A., Clinton, N., Cao, C.X., Ni, W.J., Wang, L., 2011.
625 Automated methods for measuring DBH and tree heights with a commercial scanning
626 LiDAR. *Photogramm Eng Rem S* 77(3), 219–227.

627 Hyypä, J., Kelle, O., Lehtikainen, M., Inkinen, M., 2001. A segmentation-based method to
628 retrieve stem volume estimates from 3-D tree height models produced by laser scanners.
629 *Ieee T Geosci Remote* 39(5), 969–975.

630 Hyypä, J., Yu, X.W., Hyypä, H., Vastaranta, M., Holopainen, M., Kukko, A., Kaartinen, H.,
631 Jaakkola, A., Vaaja, M., Koskinen, J., Alho, P., 2012. Advances in forest inventory using
632 airborne laser scanning. *Remote Sens-Basel* 4(5), 1190–1207.

633 Kaartinen, H., Hyypä, J., Yu, X.W., Vastaranta, M., Hyypä, H., Kukko, A., Holopainen, M.,
634 Heipke, C., Hirschmugl, M., Morsdorf, F., Naesset, E., Pitkanen, J., Popescu, S., Solberg,
635 S., Wolf, B.M., Wu, J.C., 2012. An International comparison of individual tree detection
636 and extraction using airborne laser scanning. *Remote Sens-Basel* 4(4), 950–974

637 Lefsky, M., McHale, M., 2008. Volume estimates of trees with complex architecture from
638 terrestrial laser scanning. *J Appl Remote Sens* 2.

639 Leopold, L.B., 1971. Trees and streams: the efficiency of branching patterns. *J Theor Biol*
640 31(2), 339–354.

641 Li, L., Guo, Q.H., Tao S.L., Kelly, M., Xu, G.C., 2015. Lidar with multi-temporal MODIS
642 provide a means to upscale predictions of forest biomass. *Isprs J Photogramm*
643 102:198–208.

644 Li, W. K., Guo, Q. H., Jakubowski, M.K., Kelly, M., 2012. A new method for segmenting
645 individual trees from the LiDAR point cloud. *Photogramm Eng Rem S* 78(1), 75–84.

646 Livny, Y., Yan, F.L., Olson, M., Chen, B.Q., Zhang, H., El-Sana, J., 2010. Automatic
647 reconstruction of tree skeletal structures from point clouds. *Acm T Graphic* 29(6).

648 Lovell, J.L., Jupp, D.L.B., Newnham, G.J., Culvenor, D.S., 2011. Measuring tree stem
649 diameters using intensity profiles from ground-based scanning LiDAR from a fixed
650 viewpoint. *Isprs J Photogramm* 66(1), 46–55.

651 Maas, H.G., Bienert, A., Scheller, S., Keane, E., 2008. Automatic forest inventory parameter
652 determination from terrestrial laser scanner data. *Int J Remote Sens* 29(5), 1579–1593.

653 Maltamo, M., Eerikainen, K., Pitkanen, J., Hyypä, J., Vehmas, M., 2004. Estimation of
654 timber volume and stem density based on scanning laser altimetry and expected tree size
655 distribution functions. *Remote Sens Environ* 90(3), 319–330.

656 McDaniel, M.W., Nishihata, T., Brooks, C.A., Salesses, P., Iagnemma, K., 2012. Terrain
657 classification and identification of tree stems using ground-based LiDAR. *J Field Robot*
658 29(6), 891–910.

659 Moorthy, I., Miller, J.R., Berni, J.A.J., Zarco-Tejada, P., Hu, B.X., Chen, J., 2011. Field
660 characterization of olive (*Olea europaea* L.) tree crown architecture using terrestrial laser
661 scanning data. *Agr Forest Meteorol* 151(2), 204–214.

662 Naesset, E., 1997. Determination of mean tree height of forest stands using airborne laser
 663 scanner data. *Isprs J Photogramm* 52(2), 49–56.

664 Olofsson, K., Holmgren, J., Olsson, H., 2014. Tree stem and height measurements using
 665 Terrestrial Laser Scanning and the RANSAC algorithm. *Remote Sens* 6(5), 4323–4344.

666 Popescu, S.C., Wynne, R.H., Nelson, R.F., 2002. Estimating plot-level tree heights with
 667 LiDAR: local filtering with a canopy-height based variable window size. *Comput*
 668 *Electron Agr* 37(1-3), 71–95.

669 Reitberger, J., Schnorr, C., Krzystek, P., Stilla, U., 2009. 3D segmentation of single trees
 670 exploiting full waveform LIDAR data. *Isprs J Photogramm* 64(6), 561–574.

671 Schilling, A., Schmidt, A., Maas, H. G. 2011. Automatic Tree Detection and Diameter
 672 Estimation in Terrestrial Laser Scanner Point Clouds. *Proceedings of 16th Computer*
 673 *Vision Winter Workshop*, February, pp. 75–83.

674 Schilling, A., Schmidt, A., Maas, H.G., 2012. Tree topology representation from TLS point
 675 clouds using depth-first search in voxel space. *Photogramm Eng Rem S* 78(4), 383–392.

676 Siek, J.G., Lee, L.-Q., Lumsdaine, A., 2001. *Boost Graph Library: User Guide and Reference*
 677 *Manual*. Pearson Education.

678 Simonse, M., Aschoff, T., Spiecker, H., Thies, M., 2003. Automatic determination of forest
 679 inventory parameters using terrestrial laser scanning. *Proceedings of the Scandlaser*
 680 *Scientific Workshop on Airborne Laser Scanning of Forests*, Umea, Sweden, 3–4
 681 September, pp. 251–257.

682 Sokolova, M., N. Japkowicz, S. Szpakowicz, 2006. Beyond accuracy, F-score and ROC: A
 683 family of discriminant measures for performance evaluation, *AI 2006: Advances in*

684 Artificial Intelligence (A. Sattar and B.-H. Kang, editors), Springer Berlin, Heidelberg,
 685 pp. 1015–1021.

686 Swetnam, T.L., Falk, D.A., 2014. Application of metabolic scaling theory to reduce error in
 687 local maxima tree segmentation from aerial LiDAR. *Forest Ecol Manag* 323, 158–167.

688 Tao, S.L., Guo, Q.H., Xu, S.W., Su, Y.J., Li, Y.M., Wu, F.F., 2015. A Geometric Method for
 689 Wood–Leaf Separation Using Terrestrial and Simulated LiDAR Data. *Photogramm Eng*
 690 *Rem S* 81(10), 767–776.

691 Tao, S.L., Guo, Q.H., Li, L., Xue, B.L., Kelly, M., Li, W.K., Xu, G.C., Su, Y.J., 2014.
 692 Airborne Lidar-derived volume metrics for aboveground biomass estimation: A
 693 comparative assessment for conifer stands. *Agr Forest Meteorol* 198, 24–32.

694 Wehr, A., Lohr, U., 1999. Airborne laser scanning - an introduction and overview. *Isprs J*
 695 *Photogramm* 54(2-3), 68–82.

696 West, G.B., Brown, J.H., Enquist, B.J., 1999a. The fourth dimension of life: Fractal geometry
 697 and allometric scaling of organisms. *Science* 284(5420), 1677–1679.

698 West, G.B., Brown, J.H., Enquist, B.J., 1999b. A general model for the structure and
 699 allometry of plant vascular systems. *Nature* 400(6745), 664–667.

700 Wu, B., Yu, B.L., Yue, W.H., Shu, S., Tan, W.Q., Hu, C.L., Huang, Y., Wu, J.P., Liu, H.X.,
 701 2013a. A voxel-based method for automated identification and morphological
 702 parameters estimation of individual street trees from mobile laser scanning data. *Remote*
 703 *Sens-Basel* 5(2), 584–611.

704 Wu, J.Y., Cawse-Nicholson, K., van Aardt, J., 2013b. 3D Tree reconstruction from simulated
 705 small footprint waveform LiDAR. *Photogramm Eng Rem S* 79(12), 1147–1157.

706 Xu, H., Gossett, N., Chen, B.Q., 2007. Knowledge and heuristic-based modeling of
 707 laser-scanned trees. *Acm T Graphic* 26(4).
 708 Yao, W., Krzystek, P., Heurich, M., 2012. Tree species classification and estimation of stem
 709 volume and DBH based on single-tree extraction by exploiting airborne full-waveform
 710 LiDAR data. *Remote Sens Environ* 123, 368–380.
 711 Zhao, K.G., Popescu, S., Nelson, R., 2009. Lidar remote sensing of forest biomass: A
 712 scale-invariant estimation approach using airborne lasers. *Remote Sens Environ* 113(1),
 713 182–196.
 714 Zheng, G., Moskal, L.M., Kim, S.H., 2013. Retrieval of effective leaf area index in
 715 heterogeneous forests with terrestrial laser scanning. *Ieee T Geosci Remote* 51(2),
 716 777–78.