3D Tree Reconstruction from Simulated Small Footprint Waveform Lidar

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Abstract
Lidar-based 3D tree reconstruction enables the retrieval of detailed tree structure; however, most existing methods are based on high-density discrete return lidar datasets. In this paper, we propose the use of small footprint waveform lidar data to achieve branch-level tree reconstruction for both leaf-off and leaf-on conditions. The DENSE simulation environment was used for algorithm validation purposes. Leaf-off data served as reference, and leaf-on reconstruction for a particular tree resulted in an average branch length difference of 0.07 m and an average angular difference of approximately 6 degrees for both tilt and azimuth angles. Compared to in situ methods this approach may be used by an airborne system for accurate estimation of forest biomass, forest inventory, land degradation, etc., in large scale applications. Furthermore, since this approach can also be applied on leaf-on trees, the tree skeleton characterization eventually can be conducted year round and will be less dependent on seasonal changes.

Introduction
Three-dimensional (3D) tree reconstruction algorithms have recently seen a significant upturn in research interest, mainly for environmental applications, such as improving our understanding of canopy and understory light and plant growth behavior, advancing 3D tree modeling from field-collected data, etc. (Pearcy and Yang, 1996; Cote, 2012; Livny 2011; Tang, 2013; Zhou, 2012; Li, 2012). Three-dimensional scene reconstruction has also attracted interest in the computer vision field, where trees are reconstructed from digital photographs for visualization purposes (Shlyakhter et al., 2006; Wu et al., 2011). Three-dimensional forest reconstruction has a long history of computer vision research, with the introduction of laser scanning technology for assessing 3D vegetation structure. Light detection and ranging (lidar) is one such laser scanning technology that has seen much use for assessing especially forest or woody vegetation structure (e.g., van Aardt et al., 2006; Wu et al., 2011). The advantage of lidar technology is that it captures 3D information about the tree structure, which may be beneficial to tree reconstruction (Delagrange and Rochon, 2011). Reconstruction methods reported in literature are typically focused on discrete return point cloud datasets (Sampath and Shan, 2010), i.e., a sequence of x, y, z coordinate combinations. Existing 3D reconstruction approaches, furthermore, typically rely on ground-based lidar data and then mostly for leaf-off branch reconstruction scenarios (Gorte and Pfeifer, 2004; Binney and Sukhatme, 2009).

Gorte and Pfeifer (2004) proposed a tree stem and branch reconstruction algorithm in 3D voxel space by using point cloud data (sequence of x, y, z triplets) captured with Zoller and Prohlich laser scanners. This approach is based on a variety of basic and advanced 2D raster (image) processing approaches, which are transferred to the 3D domain. These approaches include filtering, mathematical morphology, skeletonization, connected component labeling, and shortest route computation. Binney and Sukhatme (2009), on the other hand, presented a probabilistic 3D tree-branch reconstruction model and applied a generative model of a tree to guide an iterative reconstruction process. Their approach succeeded in recovering parameters such as branch locations, angles, radii, and lengths, as well as connectivity information between branches. More recently, Cote et al. (2009) proposed a modeling approach to reconstruct plausible tree structures from multiple lidar scans (co-registered 3D point cloud data). The main steps of the algorithm include: (a) point cloud segmentation in terms of separate wood and foliage components, (b) skeleton structural extraction, (c) growing of finer branching structure, (d) defining typical foliage structure, and (e) distributing foliage elements within the crown by using a light availability model. The main strength of the proposed reconstruction algorithm lies in its capacity to reconstruct the tree architectures, even when the point density or angular resolutions are low, or under non-ideal external conditions, e.g., in the presence of wind and/or occlusions of the interior of the tree crowns.

However, these reported methods from the literature typically are based on high-density discrete return or point cloud datasets from ground-based lidar systems. A direct inverse modeling approach, based on full-waveform lidar data, therefore still presents a gap in terms of lidar research. This is especially true since such ground-based lidar systems can only acquire data for a small area for vegetation reconstruction, which is not useful for ecosystem monitoring, such as forest inventory or carbon and land degradation analyses, all of which require large area sampling. We postulate that waveform lidar-based 3D tree reconstruction is well suited to addressing this challenge, given that the spatial resolution of full waveform lidar systems has seen significant improvements (e.g., less than half meter) and that such systems have the unique capability of recording laser backscatter along the entire cross section of a target, resulting in dense point cloud data sets when discretized (Wu et al., 2011).

Our approach is founded in the hypothesis that point clouds that are associated with the same object (branches, canopy, etc.) should cluster together if this object is visually separable from others in 3D space. Figure 1 shows an example...
of such a point cloud visualization, extracted from simulated waveform lidar data for tree branches on a per-voxel basis (Wu et al., 2011). We can clearly see the correlation between the point cluster and actual branch location; we hypothesize that such points can be clustered together to reconstruct the branch structure.

Numerous clustering algorithms have been reported in the literature for image processing, data mining, and other purposes. The most famous, namely the k-means clustering algorithm (MacQueen, 1967), requires knowledge of the number of clusters to classify the data using an iterative strategy to optimize the objective function, e.g., the Euclidean distance. The result is the location of the center of gravity of each cluster. The shape of the cluster is therefore restricted to be a symmetric ellipse or circle, which is rare for the point clouds that are related to natural tree branch structure in 3D space. The improved k-medoid method, CLARANS (Clustering Large Applications based on RANdomized Search) (Ng and Han, 1994), was shown to be more efficient, while the natural number of clusters also can be determined by this algorithm. However, the run time of this approach is significantly longer than, for instance, k-means clustering, which renders it unsuitable for processing large area lidar data. Other methods, such as the hierarchical algorithm (Garcia et al., 1994), iteratively split the data into smaller subsets. The advantage is that it does not require “k” (the number of clusters) as an input. However, the main challenge is the difficulty of determining the termination condition to indicate when the merge or division process should be terminated. In this paper, we propose to use “density-based spatial clustering of applications with noise” (DBSCAN) as a method of 3D clustering to achieve first order waveform-based 3D tree reconstruction (Ester et al., 1996). Note that by “first order” we imply first order branching, i.e., the tree stem and the immediate branching pattern from that stem. First, the DBSCAN algorithm will be described, followed by a presentation of the results of 3D branch reconstruction for both leaf-off and leaf-on conditions.

In terms of validation of the 3D reconstruction approach, it is evident that complete knowledge of the target, or the tree object in this case, is required. We used the Digital Imaging and Remote Sensing Image Generation (DIRSIG) simulation environment (Burton et al., 2002; Brown et al., 2005) and hypothesize that this approach can eventually be extended to actual airborne data, since (a) DIRSIG is a first-principles, validated simulation environment and (b) our 3D reconstruction algorithms were based on exactly known and accurate 3D models that served as reference for reconstructed trees.

### Methods

#### Dataset

For the methodology development and validation, we simulated the complexity and diversity of natural trees by generating six different virtual 3D trees (Figure 2) at a fine and detailed scale. Figure 3 shows the workflow of the lidar waveform simulation for a tree using DIRSIG (Wu et al., 2011). A 3D virtual deciduous tree was created as input to the DIRSIG lidar simulation by using the tree generation software Arbaro with predefined tree height, number of branch order, and leaf density (http://arbaro.sourceforge.net). Materials (leaves, branches, ground) were mapped to each facet of this 3D model and valid emissivity and extinction coefficients, which are based on measurement of actual vegetation, were assigned to each material to simulate the absorption, reflection, and transmission processes for each pulse and the vegetation it interacts with (Burton et al., 2002; Brown et al., 2005). An operationally viable waveform lidar platform was set up in the DIRSIG environment as per the system configuration lists: the goal was to match our virtual system with commercially available small-footprint waveform lidar systems, e.g., an Optech ALTM and the Leica LMS series. The plot for each tree was divided into a 40 × 40 pixel grid with a waveform footprint size equal to 0.5 m, and each simulated waveform was made up of 225 time bins with laser interactions ranging from 24.995 m (above ground) to −8.605 m (below ground) at a temporal sampling resolution of 0.15 m for each pixel. Each of these waveforms then was discretized, based on multi-modal interactions, to present a dense point cloud for each waveform along its trajectory and for the whole scene, consisting of multiple waveforms (Wu et al., 2011 and 2012).

#### Waveform Lidar Clustering

In DBSCAN (density-based spatial clustering of applications with noise), proposed by Ester et al. (1996), a cluster, which

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**Figure 1.** (a) 3D tree branches input, and (b) associated point clouds extracted from simulated waveform data.

**Figure 2.** Simulated 3D trees used for lidar waveform simulation.
is a subset of the total points, must meet the following two properties:

1. All the points within that cluster should be mutually connected in terms of density.
2. If a point is density-wise connected to any point in the cluster, this point also is a part of that cluster.

The algorithm starts with any arbitrary point in the database. The only variables that need to be defined by the user are (a) the minimum number of points required to form a cluster and (b) the radius of the neighborhood. For each point that has not been visited, its neighborhood is retrieved, and if there are enough points contained in that neighborhood, a cluster is initiated; otherwise, it is labeled as a noise point. The underlying principle of DBSCAN is that for each point of a cluster, its neighborhood should contain at least a minimum number of points or a certain point density. To detect a cluster, DBSCAN can start with any arbitrary point in the database and retrieve all associated points, based on a density parameter. The reasons that DBSCAN was chosen for tree branch reconstruction in this study are as follows: first, it does not require the number of clusters as a priori input (in contrast to the k-means algorithm); and second, the spatial shape of the branch cluster can be arbitrary, as shown in Figure 4, which allows flexibility in the branch posture.

### Stem and Branches Reconstruction

A number of assumptions were made during the implementation of DBSCAN:

- The stem can be modeled as a cone structure, where height is defined as the distance from the ground response to the highest location of the point clouds, derived from each waveform data sample. The stem center position on the x, y plane can be estimated based on the average of x, y for all the point clouds. This is based on the assumption that for regular trees, the main stem is typically located in the center of the branches.
- For the reconstruction of branches, an assumption was made that each cluster can be approximated by a cylinder to represent a branch. The two apexes of the branch are defined as the closest and furthest point within that cluster relative to the stem center. The main challenge in reconstructing a complete 3D tree in leaf-on condition using waveform lidar data is indeed the branch component. This is due to the fact that the laser pulse in the near-infrared wavelength (1064 nm) typically is not transmitted by branches inside the canopy. Therefore, the point clouds extracted from waveform lidar associated with a tree typically show the profile of the canopy.
the two apexes should also be small enough so that this branch can directly originate from the center stem. The threshold of L and $\theta$ can be defined by the user, since this value can vary for different tree species, and is also dependent on the waveform lidar settings, e.g., lidar wavelength, power, etc.

Once the first order branches were identified, the next step was to reconnect them to the stem. Figure 6 shows the side view of the first order branches, and the dashed line represents the extension of the branch to the stem. In order to maintain the same tilt angle for the branch, it can be modeled using similar triangle geometry. The position that the branch originates from can be estimated by:

$$Z = \frac{3Z_1 - Z_0}{3 - 1}$$  \hspace{1cm} (3)

$$\beta = \sqrt{\frac{X_1^2 + Y_1^2}{X_0^2 + Y_0^2}}$$  \hspace{1cm} (4)

where $(X_0, Y_0, Z_0)$ and $(X_1, Y_1, Z_1)$ are the spatial coordinates of the two apexes for that branch.

Finally, the sub-branches can be connected to the nearest neighboring branches for improved visualization. To further quantify the accuracy of the branch reconstruction, three metrics were computed to compare the reconstructed

However, these reconstructed first order branches may also be disconnected from the main stem because of the strong energy attenuation in these woody regions within a tree. Two parameters therefore were proposed to address this challenge, namely branch length $(L)$ and branch angle $(\theta)$, to first select the first order branches and then naturally reconnect them to the stem. Figure 5 shows the top view of the initial sparse branch locations using cylinders, one of which is highlighted in ellipse and labeled by “$L$” and “$\theta$”. Here, L is the length for that cluster, while $\theta$ is defined as the angle between the two apexes of that branch relative to the stem center:

$$L = |V_0 - V_1|$$  \hspace{1cm} (1)

$$\theta = \text{acos} \left( \frac{V_0 \cdot V_1}{|V_0||V_1|} \right)$$  \hspace{1cm} (2)

where $V_0$ and $V_1$ are the vectors representing the two apexes of the branch. The assumption is that the cluster size (length) of the first order branch should be relatively long compared to the sub-order branches. The projection angle, $\theta$, between
branch under leaf-on conditions to the leaf-off conditions: average azimuth angle (AA), average zenith angle (TA; tilt), and average projected branch length (BL). The azimuth angle is in the 0° ~ 360° range, and the zenith angle of the branch is defined to be 0° ~ 90°, assuming that the branches only grow upwards (Figure 7). The projected branch length is defined to be the projection length of the branches onto the x, y horizontal plane. Due to the reduced point density of the waveform data, we evaluated the accuracy per quadrant, where a quadrant is defined by an azimuth angle of (0° to 90°), (90° to 180°), (180° to 270°), and (270° to 360°). All three metrics subsequently were averaged in each region for comparison purposes.

Results and Discussion

Leaf-off Scenario

First, we consider a simple case, namely the reconstruction of a branch using the simulated waveform from a 3D tree model at the leaf-off condition. In reality, the typical outgoing pulse has a specific pulse width; therefore, when the laser pulse interacts with the target (branch), the width of reflected waveform will be increased further due to the convolution of the outgoing waveform with the target profile. This may cause difficulty in representing the object if we register every sampling point in the waveform and plot them in 3D space. In contrast to the discrete return lidar points (where only first return points are used to represent the target at that location) waveform data use many contiguous sampling points to indicate one location, which effectively amounts to data redundancy for that point in space. We therefore set a threshold for the waveform intensity to reduce the data redundancy, since typically only the waveform peak region corresponds to the most critical location of the target. Figure 8 shows a 3D representation of waveform data with different intensity thresholds by taking Tree 2 (see Figure 2) as an example, where every point is extracted from the waveform sampling and has an intensity beyond the threshold. It is evident that, if the threshold is set too high, an inadequate number of points will result in an inability to represent the branch structure. On the other hand, too small a threshold can result in data redundancy, which could make it challenging to distinguish the exact branch location. Therefore, the threshold setting is critical to ensure acceptable clustering results. As we proposed in the Methods Section, in order to maximize the detection of branches, we iteratively ran the DBSCAN algorithm with different waveform intensity threshold settings, until the maximum number of clusters was reached. Figure 8 shows the plot of number of clusters versus intensity threshold. We concluded that the threshold associated with the maximum number of detected clusters is considered optimal, since too few points will result in fewer clusters, whereas too many points located close together (e.g., the whole tree), may be grouped into a single cluster. In other words, the point where branches are clearly distinguishable will yield the most clusters. The results shown in Figure 9 corroborate the observation made based on scenarios shown in Figure 8, i.e., that there exists an optimal threshold that can return the maximum number of clusters. In this example,
the optimal threshold associated with the maximum number of clusters is 1.21, which resulted in 49 clusters. The final cluster result, based on this optimal threshold, is also illustrated in Figure 10. Different gray intensity points were used to represent the clusters that were identified. In contrast to the large-area discrete return lidar point clouds associated with typical first returns, which is sparser and does not necessarily form a branch shape in 3D space, waveform data provide more flexibility to maximize the probability of detecting the branches.

Once the data subset was chosen according to the optimum threshold, the stem was modeled as a cone structure, centered at the average of x,y for all the point clouds. The results are presented in Figure 11.

Figure 12 illustrates how the first order branches, approximated by cylinders from each cluster using DBSCAN, are modeled for a virtual tree in the leaf-off condition. The two apexes of the branch are defined as the closest and furthest point within that cluster, relative to the stem center. Finally, we reconnected the branches to the stem, using Equations 3 and 4, to enhance realism and for calculation of branch length, as shown in Figure 13.
Leaf-on Scenario

Following the same methodology as we applied for the leaf-off scenario, the results for leaf-on case, based on the same Tree 2 (see Figure 2), are presented in this section. Figure 14 shows the difference between the point clouds without any filtering versus the application of the optimal intensity threshold. The effectiveness of this threshold is evident from Figure 14b, where the internal branch cluster is much more defined. Figure 15 shows the stem reconstruction for the leaf-on case. The overall canopy shape can already be visualized at this stage.

Figure 16 shows the results of optimal DBSCAN clustering, as well as the branch representation of each cluster. Compared to the leaf-off condition for the same tree as in Figure 13, it was observed that the branch structure is similar in terms of location and tilt angle. However, for the leaf-on scenario, the branches appeared to be sparser; this was attributed to the rapid energy attenuation as the laser pulse is transmitted through the canopy.

Figure 17 shows the final results of the stem and branch reconstruction for the leaf-on scenario. In general, the first order branch structure appears to be similar, which is promising, while the leaf-off condition results in more branch/structure detail when compared to the leaf-on condition. This result is to be expected, since the canopy cluster can overlap, resulting in fewer detectable branches. On the other hand, energy attenuation as laser pulses are transmitted through the canopy can also reduce the probability of detecting the branch and leaf structure, especially in the bottom portion of the canopy.

To further quantify the difference in branch reconstruction between the leaf-off and leaf-on case, Figure 18 shows the diagram that characterizes the branch azimuth angle versus the 2D first order branch projection, and also the azimuth angle versus the zenith angle (tilt) for each branch. Each vector in the diagram represents a branch projected in the 2D x, y plane at a certain azimuth angle, while the length of the vector corresponds to the projected branch length and the tilt angle, respectively. The results are summarized in Table 1. It can be observed that the azimuth angle and tilt angle of the reconstructed branches from the leaf-on tree are each approximately 6° different from the leaf-off condition (reference data). The projected branch length was first normalized by the longest branch in the comparison, because the first order branch absolute length, derived from the leaf-on condition,
contrast to airborne discrete return lidar data, where we may not have enough information for data preprocessing. Because small footprint discrete return lidar sensors usually produce single or a few (<4) returns per pulse at the meter level footprint size, these types of data can only resolve the overall canopy shape and typically are unable to show the branch cluster shape (Chen et al., 2006; Mitchell et al., 2011; Zimble et al., 2003). Also, we characterized the branch geometry in terms of branch length (L) and branch angle (θ), by approximating the first order branch cluster as a cylinder from the clusters. Mathematically, we developed a model using similar triangle geometry to naturally reconnect first order branches to the stem. Finally, the proposed approach was applied to both leaf-off and leaf-on scenarios for first order tree branch reconstruction in a robust simulation environment (DIRSIG). This was validated by using the simulated waveform data from the same trees for these two scenarios (leaf-on versus

### Conclusions

We presented a novel 3D first order branch reconstruction approach, based on the DBSCAN clustering algorithm, that can be applied directly to waveform lidar data. An optimal waveform intensity threshold was determined by iteratively running DBSCAN across a wide range of threshold settings in order to maximize the branch clusters that can be detected. The results also show the potential of 3D object reconstruction by using corresponding simulated waveform lidar data, in contrast to airborne discrete return lidar data, where we may not have enough information for data preprocessing. Because small footprint discrete return lidar sensors usually produce single or a few (<4) returns per pulse at the meter level footprint size, these types of data can only resolve the overall canopy shape and typically are unable to show the branch cluster shape (Chen et al., 2006; Mitchell et al., 2011; Zimble et al., 2003). Also, we characterized the branch geometry in terms of branch length (L) and branch angle (θ), by approximating the first order branch cluster as a cylinder from the clusters. Mathematically, we developed a model using similar triangle geometry to naturally reconnect first order branches to the stem. Finally, the proposed approach was applied to both leaf-off and leaf-on scenarios for first order tree branch reconstruction in a robust simulation environment (DIRSIG). This was validated by using the simulated waveform data from the same trees for these two scenarios (leaf-on versus

![Figure 14. (a) Raw point clouds extract from the waveform, and (b) after applying optimal intensity threshold.](image)

![Figure 15. Stem reconstruction for leaf-on condition: (a) leaf-on tree input, (b) reconstructed stem from a side view, and (c) reconstructed stem from a top view.](image)
leaf-off) as inputs. Three metrics were computed to further validate the accuracy of the branch reconstruction for the leaf-on case: average azimuth angle (AA), average zenith angle (TA; tilt), and average projected branch length (BL). Although there exists some variation between different tree species and pulse width scenarios, the results still show a promising outcome whereby our proposed approach can reconstruct tree structure at the first order branch level with similar geometry, compared to the leaf-off scenarios for different trees.

In short, our approach shows that the first order skeleton structure inside the canopy can be successfully characterized and reconstructed using high fidelity simulated small footprint waveform lidar data, which has not been adequately addressed in the literature before. Further research should involve higher order branch reconstruction by estimating the lower order branch clusters in 3D. A local waveform intensity threshold also may be valuable to distinguish more details of the branch structure. In addition to that, advanced computer graphic techniques could be another tool to render the reconstructed branch in 3D in a more realistic way in terms of facet geometry, reflection lighting, shadow, etc. Finally, and critically, this approach eventually will be tested on real waveform data for reconstruction of forests. This research has significant implications for applications ranging from 3D scene visualization for modeling or rendering purposes, detailed biomass/carbon estimation, and vertically stratified habitat assessment.
Figure 19. Branch reconstruction results with (a) the original 3D tree model (leaf-on), (b) original 3D tree model (leaf-off), (c) reconstructed tree branches using lidar waveforms simulated for the leaf-on tree, (d) quantitative accuracy assessments for 2 ns and 4 ns pulse widths for branch reconstruction (leaf-on) in comparison to the reference data (2 ns leaf-off). Note: Azimuth Angle (AA) in degrees, Tilt Angle (TA) in degrees, Normalized Branch Length (BL).
TABLE 1. A QUANTITATIVE COMPARISON OF BRANCH RECONSTRUCTION FOR THE LEAF-OFF AND LEAF-ON CONDITIONS, WHERE “Δ” REPRESENTS THE DIFFERENCE FOR EACH METRIC

<table>
<thead>
<tr>
<th>Region:</th>
<th>Azimuth Angle (degrees)</th>
<th>Tilt Angle (degrees)</th>
<th>Normalized Branch Length</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Leaf-on</td>
<td>Leaf-off</td>
<td>Leaf-on</td>
</tr>
<tr>
<td>0°-90°</td>
<td></td>
<td>36.92</td>
<td>42.94</td>
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<tr>
<td>90°-180°</td>
<td></td>
<td>139.22</td>
<td>133.08</td>
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<tr>
<td>180°-270°</td>
<td></td>
<td>215.42</td>
<td>229.10</td>
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<tr>
<td>270°-360°</td>
<td></td>
<td>315.89</td>
<td>315.49</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>6.56</td>
<td>6.15</td>
</tr>
</tbody>
</table>

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