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Automated Individual Tree Measurement Through Morphological Analysis of a LIDAR-Based Canopy Surface Model

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Abstract—An algorithm for automated individual tree measurement was developed that is driven by a morphological analysis of a high-resolution LIDAR-based canopy surface model. Binary and grayscale mathematical morphology were used to relate structure within a three-dimensional forest canopy model to the location of individual tree crown apexes. This information was used to extract LIDAR measurements of individual tree position and height. Algorithm measurements were compared to photogrammetric measurements from large (1:3000) scale aerial photography. Given a range of “optimal” input parameters, the algorithm was successful in locating and measuring individual tree crown heights. The algorithm identified individual tree crown apexes in a mature forest with closed canopy within 2 meters of photogrammetrically-measured crown apexes with a User’s accuracy of 89% and a Producer’s accuracy of 83%. The difference between algorithm and photogrammetric tree crown apex height measurements was approximately 1 meter in both study areas.

INTRODUCTION

Forest inventory programs require detailed information on individual tree characteristics, including height, diameter, species, volume and condition. In particular, measurement of predominant tree height is a critical variable in determining stand volume as well as site characteristics (Schreuder et al., 1993). In addition, information relating to the location and dimensions of individual trees can support distance-dependent forest modeling and site-specific forest engineering design. While national and local inventories often utilize remotely-sensed data for stratified sampling and classification of general forest type, most of these programs remain heavily reliant upon expensive field data for individual tree-level information (Czaplewski, 1999). The emergence of commercially available high-resolution active remote sensing technologies, such as airborne laser (LIDAR) scanning, can potentially allow for accurate, precise, and automatic identification and measurement of individual trees composing the canopy surface.

There has been increasing interest in recent years in the development of algorithms for identification and measurement of individual trees using high-resolution digital imagery. Probably the most well known algorithm for individual tree recognition using digital imagery is a valley-following algorithm developed by the Canadian Forest Service (Gougeon, 1998). Numerous other studies have used a model-based approach to locate individual trees using synthetic tree crown image models (Pollock, 1998; Larsen, 1998). Researchers in Scandinavia have attempted to model the relationship between the spatial distribution of individual trees and the position of spectral maxima in a digital image (Dralle and Rudemo, 1997; Lund and Rudemo, 2000). Another study has utilized two-dimensional mathematical morphology to analyze the spatial structure of individual trees composing the canopy in color aerial photography (Zheng et al., 1995).

The use of airborne laser scanning for the acquisition of forest measurement data has also been an active area of research. Research efforts investigating the use of small footprint (< 1 m) LIDAR for forest measurement have primarily concentrated on estimating forest stand-level parameters (Naesset, 1997; Nelson, 1988). A study conducted in Oregon demonstrated the use of LIDAR for predicting forest stand characteristics using plot-level LIDAR heights and canopy cover percentiles, and found very strong relationships between LIDAR-derived measurements and stand parameters (Means et al., 2000). Researchers in Canada have used a probabilistic model-based approach to estimate stand height from LIDAR data (Magnussen et al., 1999). Another study related the distribution of LIDAR canopy height measurements to the vertical distribution of foliage area (Magnussen and Boudewyn, 1998). Nelson found that the shape of the individual tree crowns composing the forest canopy can have an effect on the LIDAR-based prediction of stand-level parameters (biomass, basal area, volume), as LIDAR-based forest height estimates over canopies com-
posed of elliptical-shaped crowns will be higher than height estimates over conical crowns (Nelson, 1997).

If the structural variation within a detailed LIDAR-derived canopy surface model can be related to the positions and dimensions of individual trees, laser height measurements can be acquired for dominant and codominant trees composing the canopy surface. The objective of this paper is to present an approach to automated forest measurement that utilizes a morphological analysis of the LIDAR-derived canopy surface model to recognize three-dimensional structural features associated with individual tree crowns, and to utilize this information in extracting LIDAR measurements of individual trees.

**MATERIAL AND METHODS**

**Study Site**

The data used for this study were acquired over a mature Douglas-fir (*Pseudotsuga menziesii*) forest stand in Capitol State Forest, WA. This site is hilly with elevations varying from 500 - 1300 feet with ground slopes from 0 - 45 degrees. The study area was 0.4 ha in size and was located in the control unit for an experimental silvicultural study (Figure 1). This stand exhibits a relatively closed canopy structure, with a dominant height of approximately 48 meters and a stand density of 280 trees per hectare.

**Aerial Photography**

Aerial photography at several different scales was acquired over the study area. Normal color photography at scales of 1:12000 and 1:7000 was acquired from the Washington Department of Transportation (WADOT) in June 1999. Large-scale normal color photography at a scale of 1:3000 was provided by the WADOT in June 2000. This photography was acquired with a Zeiss LMK aerial camera with a 305-cm focal length lens. Both paper prints and transparencies were acquired at all scales.

**LIDAR Data**

LIDAR (Light Detection And Ranging) is a mature remote sensing technology that can provide highly accurate measurements of both forest canopy and ground surface. A LIDAR sensor system essentially works upon the principle of measuring the time interval between the emission and reception of laser pulses, and range measurement is performed by multiplying this time interval by the speed of light, a known constant (approx. 30 cm/ns). The orientation and position of the sensor at the time each laser pulse is emitted is known through the use of an integrated inertial navigation system (INS) and a differential global positioning system (DGPS). The LIDAR data used in this study were acquired in Spring 1999 with a Saab TopEye scanning system operating from a helicopter platform (see Table 1).

The positional accuracy of LIDAR measurements is approximately 1 m for horizontal positions and 10 cm for vertical positions. LIDAR measurements were provided in ASCII text format with each data record consisting of a pulse number, latitude, longitude, elevation (meters, NAVD88), scan angle, and intensity.

**Generation of the Forest Canopy Surface Model**

A digital model of the forest canopy was generated from raw LIDAR data by extracting probable canopy-level laser returns from the data set through a filtering operation (Figures 2 & 3). This operation consisted of extracting the maximum laser return within a cell, or window, of a certain size over the entire area of interest. A canopy surface model was generated by interpolating an elevation value at each pixel of the surface model based upon the Delauney triangulation of these filtered “canopy” returns (Figure 4).

It should be noted that the pixel size of the canopy model can be different from the size of the filtering cell size. The pixel size for the canopy model should be small enough to retain local structural details of the canopy surface. A canopy surface model generated in this manner is highly sensitive to the size of the window used in filtering the LIDAR data. The use of a small filtering cell (less than 1 m) will minimize the loss of information relating to micro-level canopy features (i.e. small tree crowns) but will increase the probability of extracting laser returns that are not on the canopy surface. On the other hand, the use of a larger filtering cell (1 - 2 m) will increase the likelihood that the maximum return is in fact a measurement of the true canopy surface, but

**Table 1. Flight parameters and LIDAR scanning system settings.**

<table>
<thead>
<tr>
<th>Flying height</th>
<th>650 ft</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flying speed</td>
<td>25 m/sec</td>
</tr>
<tr>
<td>Scanning swath width</td>
<td>70 m</td>
</tr>
<tr>
<td>Forward tilt</td>
<td>8 degrees</td>
</tr>
<tr>
<td>Laser pulse density</td>
<td>3.5 pulses/m²</td>
</tr>
<tr>
<td>Laser pulse rate</td>
<td>7,000 pulses/sec</td>
</tr>
<tr>
<td>Maximum echoes per pulse</td>
<td>4</td>
</tr>
</tbody>
</table>
Figure 1. Orthophotograph with study area delineated, CapitolForest, WA.

Figure 2. Raw LIDAR data (0.4 ha study area).
Figure 3. Filtered canopy returns (0.4 ha study area)

Figure 4. Canopy surface model (0.4 ha study area)
will entail the loss of information relating to the morphology of smaller structural components of the canopy surface. Therefore, canopy models in this study were generated with a fixed pixel size (0.30 m), but over a range of filtering cell sizes (0.91 m, 1.22 m, and 1.52 m) in order to investigate the influence of the canopy surface generation procedure on the accuracy of individual tree measurement.

**Morphological Analysis of the Forest Canopy Surface Model**

Mathematical morphology (or simply morphology) provides a quantitative approach to the analysis of geometric structure within the canopy surface model. In particular, a specific sequence of binary and grayscale morphological image transformations can be used to isolate individual trees composing the canopy surface, which in turn can drive an individual tree measurement algorithm.

Although originally developed for the analysis of two-dimensional binary images, mathematical morphological theory has since been extended to three-dimensional grayscale images, where the grayscale values represent intensity or another pixel attribute, such as elevation of a surface. The operations of mathematical morphology are defined in set theoretic terms. In the morphology context, sets represent the shapes that collectively make up a binary or grayscale image. Sets in two dimensions describe the foreground of the image; in three dimensions they can describe variation within a surface. The goal of any morphological operation is to gain information relating to the geometric structure of an image by probing the image with another set, of specified size and shape, known as a structuring element. The size and shape of the structuring element is chosen according to the type of shape information to be extracted from the image. In formal terms, a morphological operation is an image transformation with the structuring element serving as the parameter for the transformation. The result of a single transformation (or morphological operation), carried out with a given structuring element, conveys information relating to the shape content of the original image. Varying the size of the structuring element can result in different image transformations and can therefore provide even more information about image content.

The basic morphological operations are dilation and erosion. If an image is represented as a set A and a structuring element as another (smaller) set B, the result of the dilation of image A by structuring element B can be thought of as showing those areas where the structuring element B hits the set A (Soille, 1999). In formal, set theoretic terms, if A and B are subsets of d-dimensional space, the dilation of a set A by B is defined as:

\[ A \oplus B = \{ c \in E^d | c = a + b \text{ for some } a \in A \text{ and } b \in B \} \]

In image processing the dilation operation is often termed “fill,” “expand,” or “grow”. The dual operation to dilation is erosion. Using the above notation, the erosion of a set A by structuring element set B will show those areas where the structuring element fits the set A. In formal terms, the erosion of a set A by a structuring element B is defined as:

\[ A \ominus B = \{ x \in E^d | x + b \notin A \text{ for every } b \in B \} \]

In image processing the erosion operator is often termed “shrink” or “reduce”. In practice, the dilation and erosion operations are used together; for example, an erosion followed by a dilation makes up another morphological operation termed an opening. The practical effect of morphological openings is to remove details in the image that are smaller than the structuring element without distorting the geometric structure of unsuppressed features. Openings therefore tend to break narrow isthmuses and remove small islands within a binary image (Haralick et al., 1987).

Grayscale morphology involves extending these notions from sets in two dimensions to functions in three dimensions. It requires defining top surface of a set and the umbra of a function. For a set A in three-dimensional space, where we consider the first two coordinates (x,y) as constituting the spatial domain and the z coordinate indicating the surface, the top surface \( T[A] \) of a set is the highest value \( z \) such that \( (x,y) \in A \). The umbra of a function \( f \), denoted as \( U[f] \), is a set made up of the surface \( f \) and everything below the surface. For a given function (grayscale image) \( f \) and three-dimensional structuring element \( k \), the grayscale dilation of \( f \) by \( k \) is defined as the surface of the dilation of their umbras:

\[ f \oplus k = T[U[f]] \oplus U[k] \]

The grayscale erosion of a function \( f \) by a structuring element \( k \) is defined as the surface of the erosion of their umbras:

\[ f \ominus k = T[U[f]] \ominus U[k] \]

We can therefore define a grayscale opening of a function \( f \) by structuring element \( k \) as

\[ f \circ k = (f \ominus k) \oplus k \]

The grayscale opening operation can be interpreted geometrically as pressing the structuring element up against the surface and sliding it underneath the entire surface. The opening of the surface by the structuring element is the highest point reached by any part of the structuring element as it slides underneath the surface (Haralick et al., 1987).

**The Individual Tree Measurement Algorithm**

If a flat disk with a specified radius is used as the structuring element in a grayscale morphological opening transformation of the canopy surface model, those areas of the canopy surface model in which the disk structuring element does not fit when pressed underneath the surface, such as the tops of conical or ellipsoidal individual tree crowns, will
be removed through the opening operation (Figures 5 & 6).

The subtraction of this opened surface from the original surface, termed the morphological top-hat transformation, will therefore isolate those areas of the canopy surface that were removed through the opening, i.e. the apexes of individual tree crowns (Meyer, 1979) (Figures 7 & 8). A thresholding operation is used to convert this top-hat transform into a binary image (Figure 9). A binary morphological opening transformation with a disk of slightly smaller size than that used in the previous grayscale opening is carried out to remove noise from this binary top-hat transform image.

This sequence of morphological operations can be carried out with a range of disk sizes to extract location of trees with varying crown widths and shapes. If these filtered binary top-hat images are added together the resulting image will contain information relating to morphological content at a variety of scales (see Figure 10). This procedure tends to aggregate areas associated with single large tree crowns, while still retaining smaller isolated features associated with smaller crowns within the image. This sequence of grayscale and binary morphological operations isolates the tops of tree crowns with distinct conical or elliptical structure that compose the three-dimensional canopy surface model (see Figure 11). With high density LIDAR data (more than 1 return/m²), the laser measurement with the highest elevation within each of the areas isolated with this morphological algorithm should provide an estimate of the location and elevation of the top of each individual tree crown composing the canopy surface. The difference between this LIDAR estimate of the location of an individual tree crown apex and a base elevation interpolated from a LIDAR-derived digital terrain model will allow for estimation of heights for the individual trees composing the canopy surface (see Figure 12).

Photogrammetric Individual Tree Measurements

Accuracy assessment was carried out through comparison to photogrammetric measurements carried out on a Carto In-
Figure 7. Top-hat transformation.

Canopy surface model

Top-hat transformation

Figure 8. Top-hat transformation of canopy surface model (0.4 ha study area).

struments AP190 analytical stereoplotter. This approach allows direct comparison of the performance of the automated tree measurement algorithm to the results expected from conventional methods based upon aerial photograph interpretation. Large-scale (1:3000) normal color photographs were used to maximize the accuracy of the photogrammetric measurements. The tops of all trees visible in the study area were measured photogrammetrically and stored as (x,y,z) point coordinates in a file. These photomeasured locations were then compared to the tree crown measurements generated by the automated algorithm.

RESULTS

The results of the accuracy assessment are summarized in Table 2. This table indicates the relative performance of the morphology-based tree measurement algorithm as parameters of the canopy surface generation process (filtering cell size) and morphological analysis (structuring element radius) are varied. Results are shown for error radii of 1 and 2 meters, where the error radius represents the maximum distance allowed for a “match” between photogrammetrically-measured trees and algorithm-measured trees. Measures of both omission error (Producer’s accuracy) and commission error (User’s accuracy) in algorithm tree identification are indicated (Lillesand and Kiefer 1994). Producer’s accuracy was calculated by dividing the total number of “matched” trees by the total number of trees measured in the aerial photographs. User’s accuracy is calculated by dividing the total number of “matched” trees by the total number of trees identified by the algorithm. In addition, the relative accuracy of the algorithm in identifying trees is shown graphically in Figure 13. In this figure, red crosses indicate location of trees identified by the algorithm, while the disks indicates the 2 meter error radius centered on the photogrammetrically-measured trees.

The elevations of the individual tree crown apexes measured from the photography and generated from the algorithm are compared in Table 2. For all “matched” trees (at both 1 and 2 meter error radii) the difference in elevation
Figure 9. Thresholded (binary) image of top-hat transform (0.4 ha study area).

Figure 10. Sum of filtered binary top-hat transforms with disks of 1.2 m (green) and 1.5 m (white) radii (0.4 ha study area).

Figure 11. Identification of tree crown apexes through morphological operations.
Figure 12. Estimation of individual tree locations and heights overlaid on DTM.

Figure 13. Accuracy assessment of algorithm. Red crosses represent algorithm measurements, circles represent 2 meter error radius surrounding photogrammetrically-measured trees.
Table 2. Accuracy assessment of individual tree measurement algorithm.

<table>
<thead>
<tr>
<th>Structuring element radii (m)</th>
<th>1 meter error radius*</th>
<th>2 meter error radius</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Accuracy</td>
<td>Mean</td>
</tr>
<tr>
<td></td>
<td>User's</td>
<td>Producer's</td>
</tr>
<tr>
<td>0.6 - 0.9</td>
<td>35%</td>
<td>92%</td>
</tr>
<tr>
<td>0.9 - 1.2</td>
<td>60%</td>
<td>80%</td>
</tr>
<tr>
<td>1.2 - 1.5</td>
<td>73%</td>
<td>76%</td>
</tr>
<tr>
<td>1.5 - 1.8</td>
<td>82%</td>
<td>64%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>1 meter error radius</th>
<th>2 meter error radius</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>Mean</td>
</tr>
<tr>
<td>User's</td>
<td>48%</td>
</tr>
<tr>
<td>Producer's</td>
<td>76%</td>
</tr>
<tr>
<td>Ht deviation (m)**</td>
<td>Mean</td>
</tr>
<tr>
<td>User's</td>
<td>83%</td>
</tr>
<tr>
<td>Producer's</td>
<td>86%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>1.5 m filtering cell size</th>
<th>2 meter error radius</th>
</tr>
</thead>
<tbody>
<tr>
<td>Terror deviation (m)**</td>
<td>Mean</td>
</tr>
<tr>
<td>0.6 - 0.9</td>
<td>53%</td>
</tr>
<tr>
<td>0.9 - 1.2</td>
<td>75%</td>
</tr>
<tr>
<td>1.2 - 1.5</td>
<td>84%</td>
</tr>
<tr>
<td>1.5 - 1.8</td>
<td>88%</td>
</tr>
</tbody>
</table>

* User's accuracy = Total # of matches within specified error radius/Total # trees identified by algorithm
Producer's accuracy = Total # of matches within specified error radius/Total # of photo-measured trees

** Ht deviation = Algorithm elevation measurement - photogrammetric elevation measurement (matched trees)

between the algorithm and photogrammetric measurements were calculated. The mean and standard deviation of the difference are given in the table.

While the results vary considerably across the range of input parameters, there is evidence that given a range of “optimal” parameters, the algorithm was successful in locating and measuring individual tree crowns. Given a specified set of input parameters (1.2 meter bin cell size, structuring element radii of 1.2-1.5 meters), the algorithm identified individual tree crown apexes within 2 meters of photogrammetrically-measured crown apexes with a User’s accuracy of 89% and a Producer’s accuracy of 83% in Area 1 (see Table 2).

DISCUSSION

Individual Tree Identification

The morphology-based tree measurement algorithm achieves accuracies comparable to other individual tree recognition algorithms that utilize high-resolution two-dimensional image data (Quackenbush et al. 2000; Stiteler and Hopkins 2000). The results indicate that the algorithm generally performs much better where tree crowns are larger and more widely dispersed. It is also apparent that the relationship between the parameter of the morphological operations – the size of the structuring element – and the predominant scale of the tree crowns composing the canopy has a direct influence on the accuracy of the algorithm. Using a smaller structuring element results in the extraction of detailed structural features within the three-dimensional canopy surface. In cases where most tree crowns making up the canopy are large, a small structuring element is too sensitive to morphological variation and will tend to extract many features, including multiple features associated with the same crown. This leads to a high commission error but a low omission error, as it tends to find the “true” tree crown apex most of the time along with many features not associated with crown apex locations. Similarly, when the structuring element is large relative to the predominant size of the tree crowns composing the canopy, the algorithm extracts large-scale morphological features that can include...
clumps of several tree crowns. This will lead to very low commission error and a very high omission error, as the algorithm tends to extract too few measurements in areas where trees are close together. There appears to be an optimal choice for the morphological parameters where the size of the structuring element corresponds to the dominant scale of the tree crown structures composing the surface, and where commission error and omission error will be minimized. The results indicate that the optimal range of structuring element scale for this mature forest, where tree crowns are relatively large, is in the range of 1.2 - 1.5 meters.

The results also indicate that the size of the filtering cell used to generate the canopy surface model does have a subtle influence on the accuracy of the algorithm. In this mature forest, with large, widely dispersed tree crowns, the optimal filtering cell size appears to be 1.2 meters.

Individual Crown Apex Measurement

The distinct advantage of using actively-sensed high-density LIDAR data over passively-sensed two-dimensional image data for individual tree measurement is the potential for individual tree stem height measurement. It is expected that photogrammetric measurement of tree apex locations from very large scale photography (1:3000) will yield very accurate estimates of the tree stem top (i.e. within a meter). The results indicate that the tree apex elevation measurements generated by this algorithm are quite close to the photogrammetric measurements, with a mean difference of approximately +/- 1 meter, with standard deviations of approximately 1-1.5 meters across all parameter ranges. The mean difference between algorithm measurements of tree crown apexes is approximately + 1 meter (standard deviation of ~ 1 m). Intuitively, given that the LIDAR was acquired in 1999 and the photography in 2000, we would expect the LIDAR to underestimate the elevation of the tree crown apexes by several feet even if all measurements were entirely accurate. There are a number of possible sources of systematic error in both LIDAR and photogrammetric elevation measurement. For example, wind causes movement of the tree top between photo exposures that can confound the precise parallax measurements that are required for photogrammetric determination of elevation. In addition, bridging ground control from medium to large scale aerial photography can be a source of error in photogrammetric height measurement.

CONCLUSIONS

This study found that mathematical morphology can be used to relate the three-dimensional structure within a detailed LIDAR-based forest canopy surface model to the location of tree crowns, and this information can be used to extract LIDAR measurements of individual tree crown apexes. The accuracy of this approach is comparable to methods that use high-resolution image data, and the use of geometric LIDAR data allows for direct measurement of individual tree heights. Further study is needed to relate these measurements to field-based tree measurements. It is expected that future work will integrate remotely-sensed individual tree measurements into sampling designs in order to optimize forest inventory programs.

LITERATURE CITED


