LIDAR-DERIVED TREE PARAMETERS FOR OPTIMAL CABLE LOGGING SYSTEM DESIGN

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Abstract: Tree location and parameters are considered fundamental information in designing logging operations. A small footprint Light Detection and Ranging (LIDAR) can provide microscale information for individual tree parameters because of high point density. Conventionally, tree parameters given by LIDAR data are estimated at the scale of inventory plots or circular sampling plots. The findings are then averaged to the whole units. However, LIDAR data can provide more microscale tree parameters such as individual tree height and tree crown diameter. In this research, we introduce an efficient method to obtain individual tree tops from a group of LIDAR points in a large area and identify tree location, which yields important information for setting skyline cableways. To achieve this, tree tops are found by the local maxima of stationary points on Digital Surface Models (DSMs). The tree tops derived from LIDAR are verified with stem locations collected in the field and displayed with Digital Terrain Models (DTMs) to show the location of trees sufficiently large to be used for skyline operation.

Key words: LIDAR, Skyline operation, Stationary Points, Tree tops.

Introduction

Airborne laser altimetry can produce maps of amazing detail and accuracy. For that reason forest engineers are beginning to use it for road location and skyline operation planning since topographic detail is likely of better quality than field-surveyed profiles (Krogstad and Schiess 2004, Schiess and Krogstad 2003). Previous research efforts have concentrated on utilizing LIDAR data for the purpose of deriving stand structure information. LIDAR technology has the promise of eventually supplanting terrestrial-based stand measurements such as forest inventory plots. Andersen and co-authors (2001) showed the promise of using LIDAR-derived stand parameters that can be used for silvicultural modeling and stand data prediction. However, a number of substantial issues still remain before LIDAR-derived stand data will replace terrestrially-derived information for that purpose.

Nevertheless, LIDAR-derived stand data do show promise in the context of operational planning. Cable harvesting and in particular cable thinning operations require tree dimensions of a certain minimum diameter. Required trees for intermediate supports and tree or stump diameter for anchoring skyline cables are a function of design payloads, terrain profile, corridor length and cable diameters. The forest engineer usually can vary or adjust most of the above design elements except for the dimensions of trees found on site. The typical design process starts with an assessment of tree dimensions which are used to arrive at the design payload and also identifies the tree size diameters across the planning unit. The latter is an important design parameter in that it impacts design payloads depending on finding the appropriately sized stump or tail tree, or the availability of the necessary intermediate support trees. Typically this information has been derived statistically. Based on stand data derived from Forest Resources Inventory System (FRIS) plots, one could estimate the average spacing of a certain tree diameter based on the number of trees above a certain diameter class. A typical process that may be used by forest engineers is outlined below to demonstrate the approach:

> “Using the Landscape Management software (LMS) in conjunction with the Forest Resource Inventory System (FRIS) data available in GIS, the number of trees per acre over 18 and 20 inches DBH was deter-mined. These diameters were chosen based on cable yarders using 7/8 inch cable typical for thinning, which requires 15 inch DBH tailholds when rigged at 30 feet. For yarders in regeneration harvests, using 1 ¼ inch mainlines, trees over 18 inch DBH were chosen for tying off at a height of 30 feet. Due to lateral yarding capabilities, we assumed corridor spacing to be 100-150 feet. This would require as few as three trees per acre with 150 foot spacing.” (Schiess and Mouton, 2005)

This approach, although statistically correct, is not spatially explicit. Harvest setting design, however, requires spatially explicit data, including tree locations with height, diameter and type of species. The presence or absence of trees with the prerequisite parameters such as sufficiently large diameters has a significant impact on whether a harvest operation is environmentally and economically successful or not.

Previous LIDAR research has shown that LIDAR-derived stand parameters can be used for silvicultural modeling. One well-known modeling program is the Landscape Management System (LMS) (McCarter, 2001). LMS can visualize stand location and simulate the growth of stands from inventory data in the context of operational planning. Another visualization tool is the FUSION program (McGaughey et al. 2003) that enables the three-dimensional display of LIDAR points. These visualization tools are very powerful, but require significant pre-processing of data to conform to the program's input requirements.

In previous research efforts, LIDAR data was analyzed with the objective of deriving the height and coordinates of tree location. Height information could be used to derive tree diameters from region-specific algorithms. In order to obtain LIDAR points describing crown characteristics of a single tree, segmentation techniques have been utilized, including the K-means method (Morsdorf et al. 2004, Riaño et. al. 2003, 2004) and watershed segmentation (Chen et. al. 2006, Sollie 2003). A marker-controlled method was especially effective in improving the absolute accuracy of the result (Chen et. al. 2006). The approach used by Andersen and co-authors was applied to a LIDAR data set to evaluate its operational application in a harvest planning project (Figure 1), (Schiess, 2005). A top-hat transformation of morphological operation (Sollie, 2002) on a binary image was used to identify tree tops. A circular filter was applied on the binary image to remove the noise on the binary image, which is given by the height of Digital Surface Models (DSMs) bigger than a certain threshold. They concluded that the size of the circular filter depends on the vertical structure of stands. Those efforts were not successful, since LIDAR-derived density estimates were not well correlated with data derived with the LMS model. The noted discrepancy could have been caused by the low LIDAR point density (3.5 pulses per square meter) and/or the necessary user input in setting the appropriate sizes and height threshold. Therefore, we took another approach to find tree tops using convexity of DSMs and higher point density data (6.5 pulses per square meter).

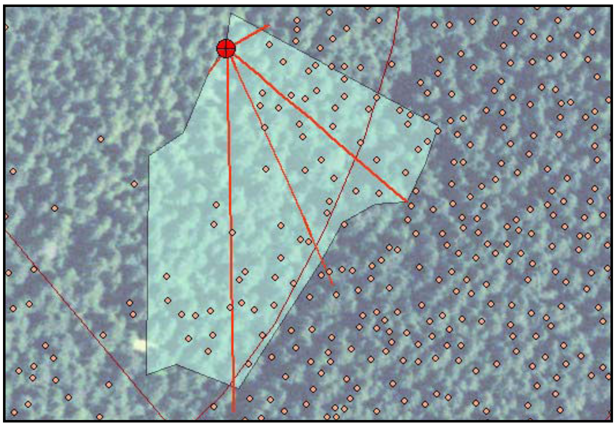

Figure 1: Harvest setting with many options for tail-hold trees derived from LIDAR data. Orange dots represent trees >15 in. DBH, red lines display yarding corridors. The harvest setting is shown as a lighter blue shading. Corridor locations and subsequent profile analysis are dictated by tree locations with appropriate diameters (Schiess and Mouton, 2005).

Improvements in the technology have facilitated more accurate methods for deriving stand structure statistics. Higher point densities for LIDAR coverage are now becoming available, with ground point densities up to 20 per square meter with current technology (Ackerman, 1999). Different approaches to processing algorithms have emerged as well, suggesting that the issues outlined above should be revisited. Therefore, we propose a new approach to obtain tree top location by using convexity of Digital Surface Models (DSMs). Such an approach allows algorithm-derived identification of tree tops rather than a user-dependent approach as reviewed above.

The objectives of our research are to:

1. Develop an efficient algorithm, independent of user input, to identify discrete tree tops, their corresponding ground location coordinates, and estimate tree height using LIDAR point data.
2. Use standard, off-the-shelf graphical software, (e.g. ArcGIS, ESRI, Inc.) to manipulate and display the results.

Data

Research Site

The research site is in the Mission Creek area, located in the Wenatchee National Forest in eastern Washington State. The main species are Douglas-fir (Pseudotsuga menziesii) and ponderosa pine (Pinus ponderosa). Summers are dry and hot, and the natural disturbance regime is characterized by frequent, low-intensity forest fires (Agee 1993).

Field Data

A total of 12 study units were established at the research site for the purpose of studies on fire and fire surrogates, including treatment plots of control, burn only, thin/burn, and thin only, with three replications per treatment (Agee et. al. 2001). Each plot measured 50 m x 50 m square. The stem locations of all the trees within the plots were measured using a differential GPS receiver (Trimble XR Pro, Santa Clara, California) and an Impulse laser rangefinder with a Mapstar compass (Lasertech, Inc., Englewood, Colorado) during the summers of 2003 and 2004 (Figure 2).

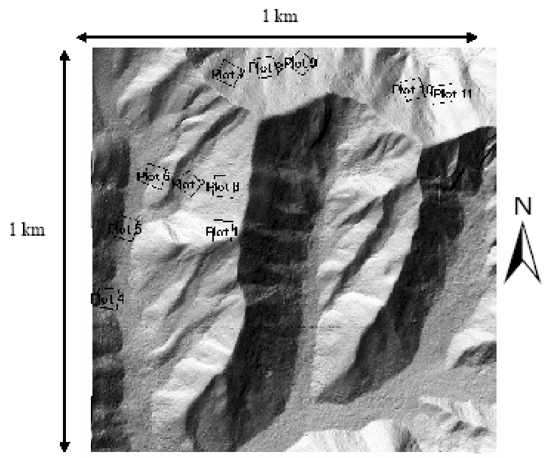

Figure 2. Plot location within a larger, 100 ha large area for which LIDAR point data exist. Stem locations are mapped for each plo*t*.

Tree species and crown position (dominant, co-dominant, intermediate, and suppressed) were recorded for all trees > 5 cm diameter in the plots. The number of trees for each crown category (dominant – suppressed) is shown in Table 1.

Table 1. Number of trees by category for the various plots. Each tree was mapped with GPS and laser units to establish their respective coordinates.

Plot #	Treatment	Dominant	Co-Dominant	Intermediate	Suppressed	Total
Plot 1	*B	17	54	33	40	144
Plot 2	*B	11	27	26	26	90
Plot 3	*B	12	21	14	16	63
Plot 4	*B	13	22	34	36	105
Plot 5	*B	14	40	26	40	120
Plot 6	*B	14	52	38	49	153
Plot 7	*TB	17	12	15	53	97
Plot 8	*TB	13	22	30	67	132
Plot 9	*TB	11	30	22	53	116
Plot 10	*TB	15	23	36	55	129
Plot 11	*TB	9	23	43	70	145
Average		13	29	28	45	117

B: burned treatment plot, TB: thinned and treatment plot.

LIDAR Data

Small footprint LIDAR data were acquired by the Optec Airborne Laser Terrain Mapper (ALTM) 30/70 LIDAR system. The coordinates of the LIDAR points were projected in Universal Transverse Mercator (UTM) Zone 10 coordinate system in the NAD83 datum. The pulse rate of the flown LIDAR dataset was 70 kHz, with a mean density of 6.5 points m-2. Table 2 shows the system settings of this sensor. The vendor-selected last returns were based on a proprietary filtering algorithm. The last returns were used to create a Digital Terrain Models (DTMs). The values on DTMs were subtracted from the ground elevation of all LIDAR points to create a Digital Canopy Height Model (DCHM) and remove any slope effect. The vendor provided text files that included all LIDAR returns. We then stored all LIDAR points in a binary file to increase processing speed.

Table 2. LIDAR sensor system settings

Date of survey	August 30th 2004
Laser sensor	Optec's ALTM 30/70
Flying height	1,000 m
Impulse frequency	70,000 Hz
Scan angle from nadir	25 degrees
Laser pulse density	6.5 pulses m^{-2}
Approximate Z accuracy	27 cm

Method

The human mind can form a mental image of a tree from un-organized, independent LIDAR points (Figure 3) by instinctively assigning points to particular trees. The methodology outlined below is designed to imitate this interpretive process.

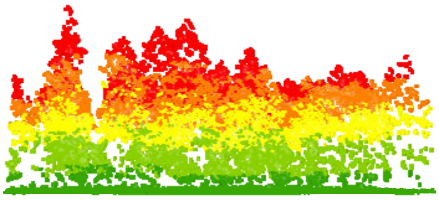

Figure 3. Raw LIDAR point distribution for a 50m x 50 m plot. Colors represent elevations. The observer can identify ground level, tree shapes and tree tops. Except for the extremes (maximum heights) tree top identification can become difficult, even for the human observer.

Research discussed earlier (Andersen et al. 2001, Chen et. al. 2006, Morsdorf et al. 2004, Riaño et. al. 2003, 2004) showed some success with algorithms that identify individual trees and their parameters, but these approaches usually require specialized software. In our approach, we convert the discrete points to DSMs, which are created from local height maxima of LIDAR points within 1m by 1m cells. To smooth the surface, a 3 x 3 Gaussian filter (Hyyppa et. al. 2001) is convolved over the DCHM layer. The 3 x 3 Gaussian filter is given by:

1/16	1/8	1/16
1/8	1/4	1/8
1/16	1/8	1/16

Tree top location is defined by the local maximum of stationary points as defined by a second order Taylor's approximation and gradient of DSMs (Bloomenthal, 1997). A value of one is assigned to cells where a local maximum of stationary points exists, and a zero value is assigned to all others. In this way, all convex shapes of the DSM are identified.

Even though all convexity on the smoothed DCHM are identified successfully, small convexities in the DCHM may be misidentified as tree tops. Moreover, holes in the connected region of the binary image may also remain because of the complexity of the DCHM. To remove these small isolated pixels, closing and opening of the morphological operation described by Sollie (2002) are conducted on the binary image.

Each region is labeled by connected component analysis (Shapiro, 2001) from the binary image after the morphological operation. From the labeled regions, LIDAR points are extracted and the maximum height among the points is recorded as the tree height for that individual tree.

Tree Top Identification

The local maxima of stationary points on DSMs is identified by using a second order Taylor's approximation and gradient of DSMs (Bloomenthal, 1997).

In the 1-dimensional case, the local maximum of function $f(x)$ is obtained by the following condition:

$$f'(x) = 0 \text{ and } f''(x) < 0 \qquad (1)$$

In the 2-dimensional case, however, the bivariate function $f(x, y) = z$ has three types of stationary points: local maximum, local minimum, and saddle points. Stationary points are distinguished by second order Taylor's approximation and gradient of function f. The second order Taylor's approximation is:

$$\begin{aligned}\tilde{f}(x,y) &= f(x_0, y_0) + (1/2)(x-x_0)^2 f_{xx} \\ &+ (x-x_0)(y-y_0) f_{xy} + (1/2)(y-y_0)^2 f_{yy}\end{aligned} \qquad (2)$$

where (x, y) is an arbitrary point on the surface and (x_0, y_0) is a fixed point on a horizontal 2-dimensional plane sliced through the LIDAR derived surface.

The parameters in equation (2) are converted to polar coordinates:

$$(x - x_0) = r\sin\theta \qquad (3)$$

$$(y - y_0) = r\cos\theta \qquad (4)$$

where ***r*** is constant and θ is angle of polar coordinate.

Using equations (3) and (4), equation (2) is recalculated to obtain $\tan\theta$ as described below:

$$\tan\theta = \frac{-f_{xy} \pm \sqrt{f_{xy}^{\ 2} - f_{xx} f_{yy}}}{f_{xx}} \qquad (5)$$

Therefore, local maxima are distinguished by the condition below:

$$f_{xy}^{\ 2} - f_{xx} f_{yy} < 0; f_{xx}, f_{yy} < 0 \qquad (6)$$

The tree top derived from LIDAR points exists within the region of local maxima of stationary points. The maximum height of LIDAR points is set as the height of a tree top within the region.

Results

Digital Canopy Height Model (DCHM)

The above algorithms created the images of tree shapes as shown in Figure 4. The area processed covered about 100 hectares. The analytically-derived tree top locations (x/y coordinates) were then compared with the field-verified stem locations.

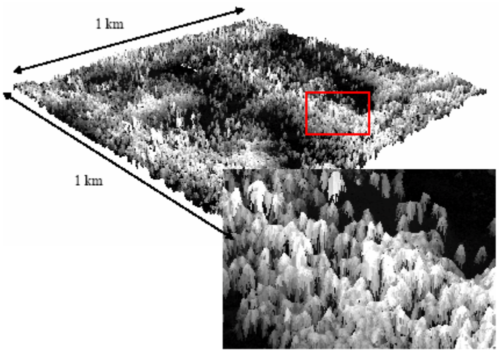

Figure 4. Digital Canopy Height Model (DCHM) covering a 100 ha area. The red box outlines a close-up view. The viewer can identify tree shapes and tree tops formed from the applied solid-surface DCHM.

Tree Top Identification

The tree tops were then identified from the DCHM. Tree heights were measured from the height maxima of LIDAR points extracted within the region of local maxima of stationary points of the DCHM (Figure 5).

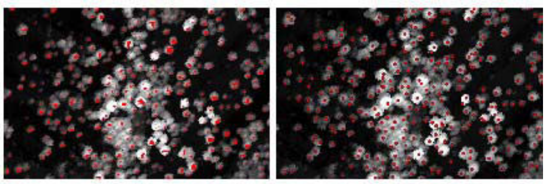

Figure 5. The region of local maxima of stationary points of the DCHM are shown as red clusters (left). The location of the maximum height of LIDAR points are identified based on the region (clusters) and displayed on the right as red points. The elevation values from the DCHM are shown with in gray-scale, with black pixels implying ground level.

We can now extract the x and y coordinates for the red dots in Figure 5 and the z coordinates, or tree heights, is extracted from the DCHM. Standard GIS query methods can now be used to stratify tree locations by height (Figure 6). If desired, tree diameter can now be derived from appropriate, region-specific height-diameter equations (Husch et. al. 2003). We have not measured actual tree heights in this research area. LIDAR-derived tree height is, however, highly correlated with field-measured tree height (Morsdorf et al. 2004).

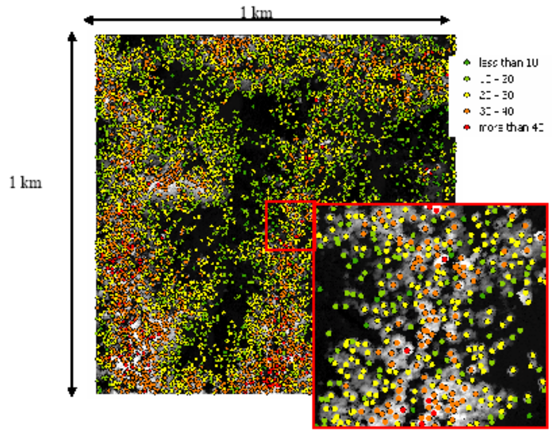

Figure 6. LIDAR-derived tree tops, color-coded by height laid over a DCHM. Tree heights (in meters) are extracted from the DCHM for each tree top. Standard GIS routines are then used to stratify (color-code) tree heights.

Verification of LIDAR-derived Tree Tops

The verification for the location of LIDAR-derived tree tops with ground data is shown in Table 3. The LIDAR-derived tree numbers are compared with the actual numbers of stems at each plot for each tree class. Dominant trees are identified with a success rate of 85%. For co-dominant trees, the success rate is 65% and then decreases to 51% and 47% for intermediate and suppressed trees respectively. However, this is not a limitation for the purposes of the method outlined in this paper, since intermediate and suppressed trees are not typically utilized as anchor points for cable logging systems (Schiess, 2005).

Table 3. Number of measured trees in each tree class for all plots. The number in parentheses indicates accuracy in percent between field-measured and LIDAR-derived tree locations.

Plot #	Treatment	Dominant	Co-Dominant	Intermediate	Suppressed	Total
Plot 1	*B	12(70)	33(61)	16(48)	18(45)	80(56)
Plot 2	*B	10(90)	20(74)	13(50)	11(42)	54(60)
Plot 3	*B	12(100)	14(66)	7(50)	6(37)	39(62)
Plot 4	*B	11(84)	12(54)	20(58)	16(44)	61(58)
Plot 5	*B	11(78)	24(60)	15(57)	19(47)	59(49)
Plot 6	*B	11(78)	27(51)	13(34)	19(38)	67(44)
Plot 7	*TB	13(76)	7(58)	3(20)	29(54)	52(54)
Plot 8	*TB	11(84)	14(63)	13(43)	29(43)	65(49)
Plot 9	*TB	9(81)	22(73)	9(40)	24(50)	63(54)
Plot 10	*TB	10(66)	17(73)	15(41)	20(36)	62(48)
Plot 11	*TB	7(77)	9(52)	16(42)	15(28)	47(40)
Total		117(85)	199(65)	140(51)	206(47)	649(45)

* B: burned treatment plot, TB: thinned and treatment plot

Conclusions

We have developed an efficient algorithm to accurately locate of tree tops. The method identified all convexities on the DCHM. In previous studies, height thresholds had to be set or established to derive binary images from DCHMs (Andersen et al. 2001). The height threshold, however, varies based on the vertical stand structure. In our approach, specification of the height threshold is no longer required.

The result shows that most of the dominant trees are identified. The intermediate and suppressed trees are not identified very well from LIDAR points, because the small footprint LIDAR returns tend to be reflected from a part of the canopy surface and not the entire canopy (Lefsky, 1999). However, for a number of forest operations planning we are primarily interested in dominant and possibly co-dominant trees. So this approach can provide a forest engineer with a tool to rapidly analyze large LIDAR data set. LIDAR data sets not only produce superb DEMs for road locations and cable load path analysis but provide additional information which has not yet been fully captured by forest engineers for harvest design purposes.

Acknowledgement

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