A FULL GIS-BASED WORKFLOW FOR TREE IDENTIFICATION AND TREE CROWN DELINEATION USING LASER SCANNING

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ABSTRACT:

Laser scanning or LiDAR data are increasingly used in forestry applications but also e.g. in urban environments or for building reconstructions. Huge point clouds are usually converted to a grid or are pre-processed in specific software packages. In this paper we present a methodology to extract and delineate single trees from small footprint, high intensity laser scanning point data in a GIS environment. Additional image data are only used for visualisation purposes and for accuracy assessment. The objective was to demonstrate the potential of a fully GIS-based workflow. After various pre-processing steps within the GIS, we developed a local maxima algorithm to identify tree tops. Secondly, we developed a region growing algorithm to delineating the respective tree crowns. It utilizes the original laser point data and not a derived raster data set such as a DSM. The algorithm was tested for six test plots located within the National Park Bavarian Forest (Germany) which is considered a natural or near-natural forest. For these plots, the results of extensive field surveys were available. Dominant trees could be detected with an accuracy of 72.2% but the overall tree detection rate was 51%. Suboptimal scan sampling distribution hinders perfect tree crown delineation. Our main goal - to develop and demonstrate a complete GIS-based workflow from Laser data pre-processing, algorithm development, analysis, to visualisation etc. – was reached. However, locating and counting trees within the LiDAR point cloud, particularly in multi-tiered deciduous plots and juvenile stands, requires the assistance of field-validation data and some subjective interpretation.

1. INTRODUCTION

Laser scanning survey technology, or LiDAR (light detection and ranging), takes advantage of the constancy of the speed of light by transmitting laser pulses from a known source to a target and timing the period between pulse transmission and reception of the reflected pulse (Bachman 1979). While the term “LiDAR” is commonly used in North America and predominantly in international journals, the German speaking research community mainly refers to “Laser scanning”. While the underlying basic concepts originated in the 1980ies, methods to systematically process 3D point clouds are relatively young. For instance, Baltsavias (1999a) and Wehr and Lohr (1999) provide basic formulas which are used widely.

Since the mid to late 1980s, the use of LiDAR for forestry applications has advanced with technology. For example, research using early generation airborne LiDAR sensors has been directed towards forest inventory surveys (Aldred and Bonner 1985), timber volume estimation (Maclean and Martin 1984), and forest canopy characterization (Nelson et al. 1984). Various researchers demonstrated the applicability of profiling LiDAR for the estimation of stand heights, crown cover density and ground elevation below the forest canopy (Aldred and Bonner, 1985). MacLean and Krabill (1986) also noted that the application of LiDAR for estimating forest attributes and terrain mapping may be possible as the amplitude waveforms of the reflected laser energy from a forest canopy exhibited similar characteristics to waveforms recorded from mapping bathymetry. For a comparison of LiDAR to photogrammetry, the reader is referred to Baltsavias (1999b). Given the ability to accurately measure topography, it was realized that certain forest attributes could be quantified from forest canopy profiles derived from LiDAR data. Specifically, various forest attributes can be directly retrieved from LiDAR data, such as canopy height, subcanopy topography, and vertical distributions of canopies. Attributes that can be predicted using empirical models from LiDAR data, include above-ground biomass, basal area, mean stem diameter, vertical foliar profiles and canopy volume (Dubayah and Drake, 2000; Lim et al., 2003a).

More recently, several researchers have applied new generation commercially available discrete pulse airborne LiDAR sensors to the task of stand-level tree height estimation (e.g. Magnussen and Boudewyn 1998), height-based timber volume estimates (e.g. Næsset 1997; Lim et al. 2003a) and, most recently, species differentiation (Holmgren and Persson 2004). Riano et al. (2004) presented a methodology for estimating crown fuel parameters at individual tree and plot levels in an intensively managed, homogeneous Scots pine forest. Andersen et al. (2005) present and evaluate an approach to estimate several critical canopy fuel metrics, including canopy fuel weight, canopy bulk density, canopy base height, and canopy height, using high-density, multiple-return LIDAR data collected over a Pacific Northwest conifer forest.

With the advent of commercial systems (Wehr and Lohr 1999; Lim et al., 2003b) a significant increase of empirical studies and the development of analysis algorithms and methodologies can be observed for the years 1999 and 2004. General knowledge and widely used algorithms have been developed. For instance, it is widely known that airborne LiDAR estimates of tree heights tend to slightly underestimate ground-truth measurements. Knowing such facts and having access to many literature studies one can easily adopt LiDAR based estimates. Various remote sensing systems and techniques have been explored for forestry applications and are reviewed e.g. by Wulder (1998), Lefsky et al. (2001) with a comparison of various remotely sensed data sources with LiDAR or by Lim et al. (2003b). Typically, most optical sensors are only capable of providing detailed information on the horizontal distribution and not the vertical distribution of vegetation in forests. LiDAR remote sensing is capable of providing both horizontal and vertical information with the horizontal and vertical sampling dependent on the type of LiDAR system used and its configuration (i.e., discrete return or full waveform LiDAR). The sensor technology used in the paper is a fiber scanner of the company TopoSys which is widely used throughout Europe. Schnadt and Katzenbeisser (2004) comprehensively describe the technology behind a fiber scanner and why this technology is suitable for edge detection and forest penetration. For a summary of research into airborne LiDAR technology for forest mensuration purposes, the reader is referred to Lim et al. (2003b).

Several studies for single tree detection using Laser scanning data already exist, e.g. Holmgren and Persson (2004), Brandtberg et al. (2003), Morsdorf et al. (2004) and Pitkänen et al. (2004). These and many other studies are mainly working with surface and terrain models derived from the laser data to extract and identify trees. In contrast we developed an algorithm that works on (pre-processed) laser point data only. Reasons for this are twofold: First we wanted to avoid under- or overestimation of tree heights due to interpolation of a raster surface. Secondly, the developed algorithm uses a sorting mechanism for point data for a more accurate delineation of single tree crowns (details see chapter 2.4).

2. MATERIAL AND METHODS

2.1 Test Site

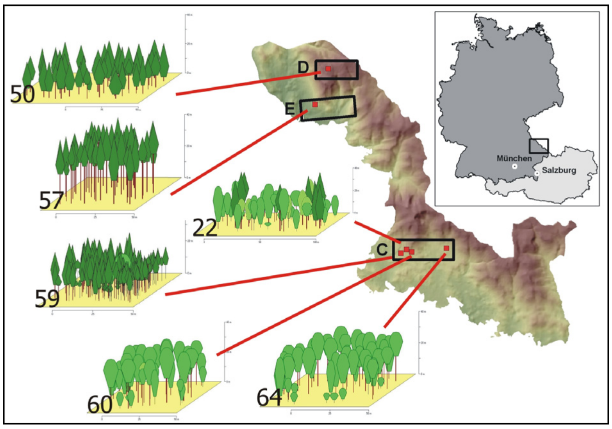

Fig. 1: Study area with 6 Silva models based on field measurements of the dominant tree crown locations.

The mapping experiments described herein were conducted on six plots in the Bavarian Forest national park which is located in south eastern Germany along the border to the Czech Republic. Three major forest types are present in the park: mountain spruce forest with *Picea abies* and some *Sorbus aucuparia* above 1100 m, submontane mixed forest with *Picea abies*, *Abies alba*, *Fagus sylvatica* and *Acer pseudoplatanus* on the slopes between 600 and 1100 m and spruce forest in moist depressions in the valleys where cold air may collect. Much of the mountain spruce stands were severely attacked by the spruce bark beetle (*Ips typographus*) in the 1990s. To capture some of the different canopy characteristics, six plots were chosen from a set of 44 reference sites established either between 2001 and 2002, or as part of a longer term permanent sample plot scheme. The plots are distributed within four test areas each with an overall size of 30 km^2 (Figure 1). Airborne data and imagery were collected for each of these areas. A more comprehensive description of the study site can be found in Heurich et al. (2003).

2.2 Data and pre-processing steps

The size of the six test plots varied from 20 by 50 to 20 by 100 meters. In each of the sites every tree position was measured in the field with an accuracy of several centimetres. For each tree higher than 5 meters DBH (Diameter Breast Height), height and starting point (base) of the crown were measured separately.

The airborne LiDAR system "Falcon" from TopoSys GmbH was used to survey the test areas on three dates: leaf-off (March and May, 2002) and leaf-on (September 2002). The TopoSys System is based on two separate glass fibre arrays of 127 fibres each. Its specific design produces a push-broom measurement pattern on the ground. For further details see Wehr and Lohr (1999) and Schnadt and Katzenbeisser (2004). The average point density for these flights was 10pts/m². First and last pulse data were collected during the flights. The datasets were processed and classified using TopPit (TopoSys Processing and Imaging Tool) software to interpolate a Digital Surface Model (DSM) and a Digital Terrain Model (DTM) both with a resolution of 0.5 m.
First and last pulse data of the summer flight were used to extract and delineate single tree crowns. Through several image processing steps original LiDAR pulses were prepared for import in a GIS software environment. Various techniques were used to process the original point data. These steps include the merging of the single flight data sets, the generation of relative heights by subtracting DEM values from LiDAR point data, the correction of negative respectively error values in the resulting data sets and various GIS data integration steps (cf. Blaschke et al. 2004a).

Simultaneous to the LiDAR range measurements, image data were recorded with the line scanner camera of TopoSys, which were used only for the following visual accuracy assessment and for some illustration purposes in this paper but not for the tree identification and analyses described herein. The camera provides 4 channels: B (440-490 nm), G (500-580 nm), R (580-660 nm) and NIR (770-890 nm). Ground resolution was also 0.5 meters.

Sensor type	Pulsed fibre scanner
Wave length	1560 nm
Pulse length	5 nsec
Scan rate	653 Hz
Pulse repetition rate	83.000 Hz
Scan with	14.3°
Data recording	first and last pulse
Flight height	800 m

Table 1: System parameters for the Laser Scanner flights.

2.3 Step 1: Tree detection

After all pre-processing steps only the raw Laser point first pulse data were used for the first part of the analysis, the identification of single trees through finding local maxima. The DTM derived by TopoSys was only used for the pre-processing to calculate the relative heights for the LiDAR point data. It is important to note that the identification of the single maxima is not an end in itself in our approach but it is necessary to subsequently derive tree crowns by applying region growing algorithms.

To filter the single trees out of the enormous amount of LiDAR points (in our study about 10 to over 20 returns per square meter (first & last pulse together)), we developed a local maxima method in a GIS environment. The used *tree finding algorithm* is based on a *regression model* (cf. Pitkänen et al., 2004; Hasenauer, 1997; Kini and Popescu, 2004) linking the crown-width to the tree-height:

$$CD = a + b*TH$$

Where: *CD* = maximum diameter of a tree crown (in m) and *TH* = tree height (in m)

The result is a local maximum search algorithm with a dynamic search radius, depending on the z (tree height) value of the analysed point. The assumption 'the higher a tree, the bigger is its crown width' has to be calibrated for the specific conditions (forest density, different climatic conditions etc.), which are influencing the crown width coherence. The model in our approach is calibrated for the average tree/crown proportion in the test area. Due to the very heterogeneous forest structure in the National Park Bavarian Forest (mixed forests, different age classes…) the formula is a more robust compromise and is not calibrated for special species or specific structures. The final parameters used were a= 1.54 and b= 0.123. Using these values in the formula mentioned above, the smallest possible detectable tree crown width is 1.54 m. Clearly, in very dense stands and/or juvenile stands this can lead to an underestimation of the amount of trees (cf. accuracy assessment for plot 59 in chapter 3).

The developed algorithm selects the first point in the GIS point data layer and searches for higher points within the maximum distance (the crown-radius) calculated by the formula. If the selected point is the highest within this restricted neighbouring area, it is interpreted as a treetop and gets stored in a new table. This procedure is repeated for every point and all tree tops found are stored in a table. The algorithm has to take into account all the LiDAR point data. It is obvious that this method can be time consuming (highly depending on the size of the plot and the dense / amount of the LiDAR points). To speed up calculation time, a moving window method is used to reduce the number of LiDAR points for the local maximum search. The test area is devided into small tiles (in this case 1 x 1meters). The moving window analysed the respective window maximum and reports it to the window centroid including the points original x,y,z values to keep the accuracy of the measured LiDAR points (cf. Blaschke et al., 2004a). With the aid of the moving window analysis only the highest point per square was used to find the single trees which results in a point reduction by at least the factor of 10 and a visible acceleration of calculation time.
This approach is lossless, as the smallest possible crown width is 1.54 meters (according to the calibrated formula), therefore no dominant tree will be lost by using a moving window size of 1x1 meter. By means of this approach it was possible to separate the dominant trees (in our test area: usually higher than 10 meters in dense forest) with adequate time and accuracy. Due to the complex forest structure of the test sites, the detection of understory trees was not very successful.

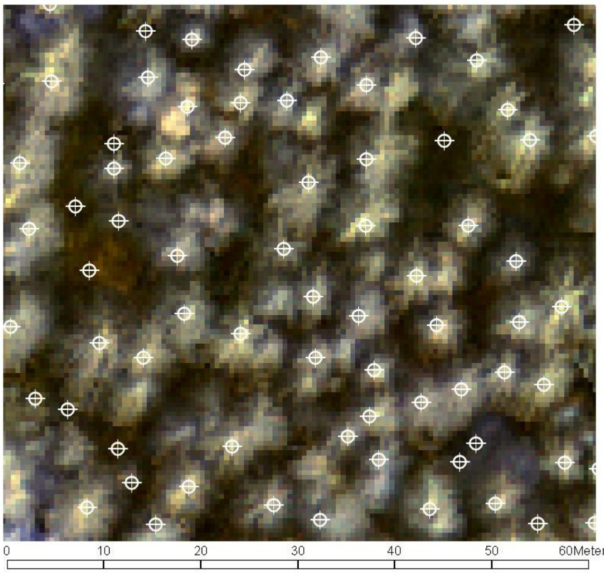

Fig. 2: Results of step one: found tree tops with underlying image data.

2.4 Step 2: Crown delineation

The resulting local maxima were used as seeding points to delineate the corresponding tree crowns. For this purpose, we developed a region growing algorithm. As discussed earlier, there are plenty of algorithms available with various pros and cons (for a recent overview on image segmentation see Blaschke et al. 2004b). Starting from the treetops, every nearest neighbour point is compared with the initial point. Nearest neighbours are defined as the 8 neighbouring moving window centroids (see below).

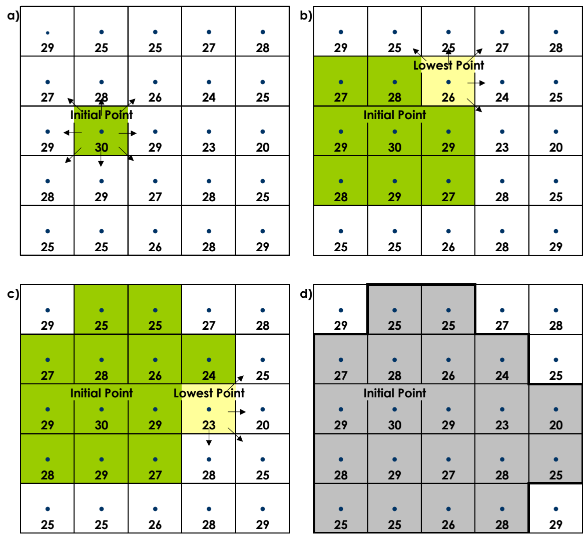

Fig. 3: a) the Initial Point (local maximum); b) comparing which of the 8 neighbours (max-window-centroids) has a lower z-value, assigning the Tree IDs and selecting the lowest point; c) repeat step b until one of the stopping criteria is reached; d) delineated tree crown.

Figure 3 illustrates the interactive principle of the algorithm: as long as the value of the LiDAR point under consideration is lower than the value of the initial point, the ID of the seed point (local maximum) is stored in the table for this laser pulse. The algorithm uses only the moving window centroids from *Step* 1 to avoid misclassification through laser point returns from below the surface. To make sure that points from smaller trees are not misleadingly assigned to higher ones, the algorithm starts with the smallest tree and stops with the highest. This is achieved by sorting the growing point table automatically before each new iteration in an ascending order. In contrast to crown delineating algorithms using raster datasets, this is one important benefit of using point data. In addition, there are three additional stopping criteria implemented in the region growing algorithm to avoid inappropriate delineations especially in dense forest stands:

- If the height value of a point is lower than 5 meters it will not be assigned to any tree (crown) which limits the lowest possible tree that can be found to this height. This limitation is necessary to avoid points from understory trees which were not found by the local maxima method to get assigned to a "wrong" tree.
- If the height value of a point is lower than 75% of the value of the respective treetop the point is not assigned. This criterion should improve wrong delineations in preliminary versions of the algorithm, where delineated regions included also smaller trees directly affiliated to much higher neighbours.
- Setting a limit for the maximum crown width. We had the best results with a region growing limit of 10 metres in every direction.

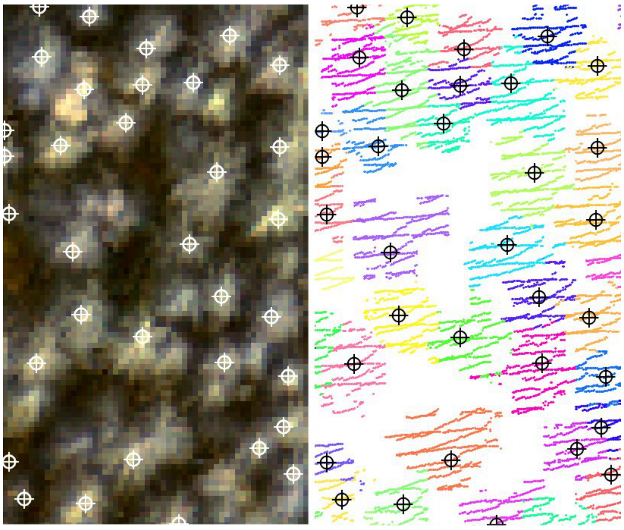

Fig. 4: Delineated trees in LiDAR point data: local maxima (left) and assigned laser point data (right).

3. RESULTS

As commonly known, LiDAR point clouds are huge data sets. Due to computer advances they are becoming more and more common in normal PC-based computer environments and consequently more seamlessly integrated in geospatial workflows. In this paper we wanted to demonstrate a fully GIS-based workflow. At least for smaller subsets of the data we could prove that the enormous amount of LiDAR data can be handled within a GIS environment if certain point filtering methods are used.
The used local maxima method works best in well spaced, mature conditions where we were able to find more than 92% of all trees higher 10 meters (*plot 64*). Correspondingly good results are achieved for the well spaced matured spruce forest in *plot 50* (> 82%). In the less spaced *plots 22, 57* and *60* the identification rates are dropping noticeably (52%, 66% and 51%) for all trees but they show still good success rates for the identification of the dominant trees (78%, 68% and 66%).

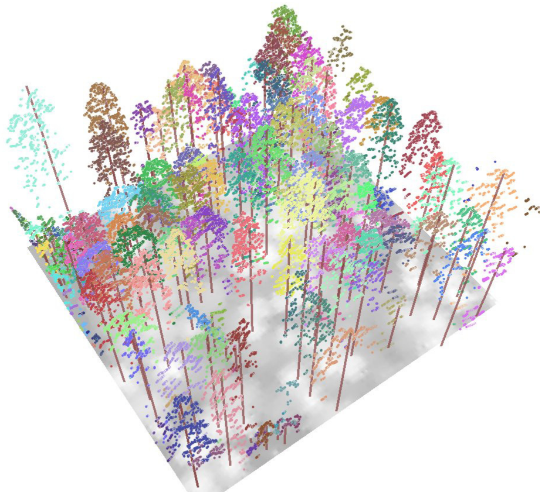

Fig. 5: 3D scene of the assigned point data with extruded local maxima illustrated graphically as tree trunks.

The proportion of all trees found in the sample plots was only about 51%. In total, we were able to find 192 out of 266 dominant trees (72.2%). The main reason for the relatively low overall detection rate is caused by one outlier (*plot 59)* where only 28.8% of all trees were found (59.5% dominant trees). This mainly depends on the juvenile, very dense forest structure (up to 2 trees per square meter) in *plot 59* (without this untypical plot – at least for the National Park – the overall detection rate would be 68% of all trees). At the moment the used formula limits us to find only one tree per 1.54 meters, the density of the stand and the percentage of the detected trees is inversely related.
Obviously the local maxima method is best suited to find dominant trees (cf. Maltamo et al., 2004 and Pitkänen, 2001). The accuracy assessment for the dominant trees therefore resulted in values of 72.2% and even 77.5% without the outlier *plot 59*. For well spaced, old stands like *plot 64* and *plot 50*, the detected trees reached values between 81% and 92% for the dominant trees. In total we got quite a low error of commission (false positives) of approx. 2%.

The accuracy assessment for the delineation of the tree crowns was carried out only visually so far (cf. discussion chapter). A first qualitative visual accuracy assessment shows promising results (Figures 4 and 5). Not all laser points could be assigned to the respective tree. These critical points were not taken into account. We tried to calibrate the algorithm "conservatively" to assign all corresponding points and by accepting to loose a few points rather than to get wrong assigned laser points.

4. DISCUSSION AND OUTLOOK

We developed algorithms to identify and delineate individual trees and presented a workflow that allows us to analyse LiDAR point data within a GIS environment. Using comprehensive and spatially highly accurate field survey data we could verify the results of the study and regard them to be satisfactory. As stated above, the overall detection rate of 51% of all trees (72% of the dominant trees) may sound low to the reader but compared to other results documented in the literature, the figures are acceptable. For instance, Heurich et al. (2004) detected about 44% of all trees in the same study area (Bavarian Forest National Park), Maltamo et al. (2004) detected about 40% of all trees in a boreal nature reserve and Tiede et al. (2004) applied an object-based image segmentation approach on the same plots with a detection rate below 50%.

Sample plot	Field measured trees		Lokal Maximum - calculated Trees			Perc. of found trees		
	All trees	Dominant trees	All trees	Dominant trees	false positives	All trees	Dominant trees	false positives
Plot 22: mature mixed (200 y) valley -side forrest	57	32	30	25	0	52,6%	78,1%	0,0%
Plot 50: sub -alpine, well spaced mature (130 - 190y) spruce	46	43	38	35	1	82,6%	81,4%	2,6%
Plot 57: mature (90 - 105y) spruce stand	45	44	30	30	0	66,7%	68,2%	0,0%
Plot 59: juvenile (30 - 50y) spruce stand	177	79	51	47	0	28,8%	59,5%	0,0%
Plot 60: mature (110 y) beech, valley side	43	30	22	20	1	51,2%	66,7%	4,5%
Plot 64: mature (100 y) beech, vellay side	40	38	37	35	2	92,5%	92,1%	5,4%
Sum of all plots:	***408***	***266***	***208***	***192***	***4***	***51,0%***	***72,2%***	***1,9%***
Sum without Plot 59:	***231***	***187***	***157***	***145***	***4***	***68,0%***	***77,5%***	***2,5%***

Table 2: Accuracy assessment for the six test plots (trees higher than 10 meters are taken into account)

The biggest problem at the moment is the unbalanced distribution of the laser points in the used data sets. Although the laser points are located almost every 10 centimetres within the flight direction, there are gaps of more than one metre perpendicular to the flight direction. In our study this results in two main problems:

- Many "real" treetops may be missed by the Laser scanner
- The dispersion algorithm for delineating the crowns returns some no data-values, which leads partly to small holes in the delineated crowns shapes

It is important to note that comparing the tree location maps using the technique described was carried out to facilitate tree-level comparisons of manually measured and LiDAR-derived metric information. This was not carried out to test the utility of the TopoSys sensor for tree stem mapping. Although it should further be noted that with refinements of the techniques used here and feature recognition algorithms, automated stem mapping and tree extraction from the LiDAR-3D point cloud data are conceivable and should be evaluated more thoroughly.

When working in a GIS environment the "classic" accuracy assessment techniques from remote sensing are not fully satisfying. Especially for quantifying the accuracy of delineated tree crowns the questions are: when can we identify an object in one data set as being the same object in another data set? Do we need user-defined or application-specific thresholds for geometric overlap, shape-area relations, centroid movements, etc? (cf. Blaschke, 2005)

Currently, additional studies are ongoing which include an object-based accuracy assessment to compare automatically delineated crowns and manually delineated crowns by an interpreter with the help of a new tool called LIST (Lang et al., submitted).

Another goal for future work is, to test the algorithms not only in other study areas (perhaps a transfer to more homogeneous forests can return even better results) but also with other Laser scanning data. It would be especially important to compare and validate the results to datasets with a lower point density.

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