ADAPTIVE METHODS FOR INDIVIDUAL TREE DETECTION ON AIRBORNE LASER BASED CANOPY HEIGHT MODEL

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ABSTRACT:

One problem of individual tree detection on aerial images or on raster canopy height models is handling of tree crowns of different sizes. On laser scanner data one size attribute, height, is directly available. This gives possibilities to develop processing methods that adapt to the object size. In this study, three adaptive methods were developed and tested for individual tree detection on canopy height model (CHM). The CHM of 0.5 m pixel size was computed from dense first-pulse point data that was acquired with a small-footprint airborne laser scanner. The field data consisted of 10 tree mapped field plots in Kalkkinen, southern Finland. The plots were mainly on mature, heavily stocked forest stands, many of which had multi-layered canopy structure. In the first method, the CHM was smoothed with canopy height based selection of degree of smoothing and local maxima on the smoothed CHM were considered as tree locations. In the second and third methods, we utilised crown diameter predicted from tree height. The second method used elimination of candidate tree locations based on the predicted crown diameter and distance and valley depth between two locations studied. The third method was modified from scale-space method used for blob detection. Instead of automatic scale selection of the scale-space method, the scale for Laplacian filtering, used in blob detection, was determined according to the predicted crown diameter. The presented three methods are compared based on the accuracy of individual tree detection. Differences of the proposed methods considering tree crown delineation by segmentation methods are discussed.

1. INTRODUCTION

One problem of individual tree detection on aerial images or on raster canopy height models is handling of tree crowns of different sizes. When a crown of specific size is processed, the image should be on appropriate scale for the interpretation of crowns of that size. On aerial images it is difficult to know the tree size beforehand, but on laser scanner data one size attribute, height, is directly available. This gives possibilities to develop processing methods that adapt to the object size.

Automatic scale selection for feature detection has been a subject of interest in computer vision. A widely used method for blob detection with automatic scale selection is based on scale-space representation and Laplacian filtering (Lindeberg, 1998). In tree detection on a CHM, local adaptation has been done at least by adjusting the window size used for finding local maxima (Popescu et al., 2002) and by choosing different scales, produced by Gaussian filtering, in different parts of the image (Persson et al., 2002). Popescu et al. (2002) used crown width predicted from tree height to give appropriate window size to search for tree tops.

One problem of local maxima method in tree detection on a CHM is the absence of a maximum in some trees even if the trees can be otherwise seen. For example, if the top of a smaller tree is near the branches of a tall tree, the smaller tree does not necessarily create a local maximum on the CHM. Still, the smaller tree may be visually distinguishable based on the shape and spatial distribution of the smaller height values from its crown. It may be possible to find more trees if pixels that are almost local maxima are also accepted as possible tree locations. This was tried in this study. Predicted crown width as a scale indicator was used also in elimination of possible tree locations and in scale selection of Laplacian filtering.

In this study, three adaptive methods for individual tree detection on canopy height model are presented. The accuracy of tree detection is tested on mapped tree data of ten field plots, located in southern Finland.

2. MATERIAL AND METHODS

2.1 Field data

The test site was in a state owned forest area of approximately 50 hectares in Kalkkinen, southern Finland. Field data consisted of individual tree measurements made on 10 systematically located sample plots, established on the test site in summer 2001. Eight of the plots were 30 m by 30 m in size, one was 25 m by 25 m and one was 30 m by 40 m. All trees having a diameter at breast height (DBH) of more than 5 cm were mapped and tree species, DBH, tree height, and height to the living crown were registered. Each tree was also subjectively classified to belong or not to belong in the dominant layer. To help tree mapping, a grid of 10 m by 10 m was first marked by setting measuring tapes on the ground in each plot. Tree stem locations were then mapped to a local co-ordinate system of the plot using the grid and additional measuring tapes. A Real-Time Kinematic (RTK) GPS was then used to measure the co-ordinates of the corner points. If the RTK GPS did not succeed in giving the co-ordinates due to insufficient visibility of GPS satellites, a tacheometer was used to measure the corner points.

The plots were on mature, mainly heavily stocked forest stands. The stand age was 78-100 years and the height of basal area median tree was 17.7-30.3 m. Average stand volume was 336 m3/ha and it varied from 127 to 533 m3/ha. The dominant tree species was Norway spruce on seven plots, Scots pine on two plots and birch on one plot. The total number of measured trees in the plots was 709, of which 412 were in the dominant canopy layer and 297 in other class. In most of these stands, there have been no cuttings in recent decades and thus many of the stands had multi-layered canopy structure.

2.2 Laser scanner data

Laser data for the study area was collected on 15 June 2000 using an airborne Toposys-1 laser scanner. The flight altitude was 400 m above ground level, giving a swath width of approximately 100 m and a nominal sampling density of about 10 measurements per m^2. The first-pulse point data was processed to get a raster canopy height model (CHM). The CHM was calculated as the difference between a digital surface model (DSM) and a digital terrain model (DTM). The DSM was obtained by taking the highest value of all laser hits within each pixel and then interpolating the value for missing pixels. First-pulse data were applied also in DTM generation since this proved to be successful in boreal forest in an earlier study (Hyyppä et al. 2000). To get the DTM, an iterative method, consisting of ground hit classification and interpolation of terrain surface (Hyyppä and Inkinen, 1999), was used. The CHM was processed to have pixel size of 0.5 m.

2.3 Methods

Crown width model: Three adaptive methods were tested for individual tree detection on the CHM. Two of the methods needed a model for tree crown width as a parameter. In the model, crown width is predicted from tree height. Least median of squares regression was used to get parameters *a* and *b* for the simple model

$$cw = a + bh \tag{1}$$

where cw = maximum width of a tree crown, m
h = tree height, m

Because crown diameters were not measured in the current test site, sample trees from another test site (a total of 364 trees) (for more details of that site, see Pitkänen, 2001) were used to get parameters for a first model. The original parameters *a* and *b* were 1.21 and 0.143, respectively. The model was calibrated visually for the current test site by plotting circles sized according to the model in the locations of trees on the CHM. The maximum width of a tree crown was then treated as a tree crown diameter. The final parameters used were then 1.20 and 0.16.

Method 1 (HBF): In the first method, the CHM was smoothed with canopy height based selection of degree of smoothing and local maxima on the smoothed CHM were considered as tree locations. Five Gaussian kernels were used so that the kernel size increased along the height of pixel being smoothed. Smallest and largest σ values were selected by looking visually that the number of local maxima was reasonable at both ends of the tree height range. The height ranges and corresponding σ values used were 0-6 m σ 0.4; 6-14 m σ 0.6; 14-22 m σ 0.8; 22-30 m σ 1.0 and over 30 m σ 1.2. The method is later referred as height based filtering (HBF).

Method 2 (ELIM): Second and third method used crown width model (Eq. 1) as a parameter affecting the adaptation to the tree size. The basic idea of the second method is first select an abundant number of possible tree locations on the CHM, i.e. local maxima or almost local maxima, and then reduce the number of these locations firstly based on slopeness within the assumed crown center area and secondly based on the distance and valley depth between a location and its neighbouring locations. The details of the algorithm are

- Create a slightly smoothed CHM. For this, Gaussian filtering with σ 0.6 was used.
- Calculate a maximality image from the smoothed CHM: for each pixel, count the number of smaller CHM values among the 8 neighbour pixels and set the count as value
- Set a threshold *Tmax* and keep only *Tmax* and larger values within the maximality image and set other pixels to 0. *Tmax* was selected to be 7.
- For each pixel location that is >0 in the maximality image, check slopeness within the assumed crown center area on the CHM: Calculate tree crown radius for the pixel studied (center pixel) from the CHM height. Calculate slope for each pixel that is within the distance of *Tdist* per cent of the crown radius and is smaller than the center pixel. If the percentage of smaller crown center area pixels exceeding slope threshold *Tslope* is larger than *Tp*, set the center pixel value in the maximality image to 0. *Tdist* was selected to be 60%, *Tslope* 4.5 and *Tp* 20%.
- Create location candidate image by finding local maxima in the maximality image. Multipixel maxima are reduced to one pixel, located in the center of the maximum studied.
- Sort location candidates and their height values from the CHM into a list in decreasing order by maximality and by height value.
- Go through the candidates in the list order and for each not removed candidate (center candidate), check any lower priority candidates within an elimination distance for removal. For real local maxima (*Tmax* = 8), the elimination distance was the crown radius of the candidate studied and 1.1 times crown radius for non-maxima. For a lower priority candidate, calculate a comparison distance as a sum of the vertical distance and depth of possible canopy valley on the CHM between the center and lower priority candidates. If the comparison distance is smaller than the elimination distance, remove the lower priority candidate. The location of the possible valley between two candidates was found by drawing three pixels wide line between the candidates, calculating median for each transverse three pixels group and finding the location of the minimum median value.

The method is referred as maxima elimination (ELIM).

Method 3 (LAP): The third method was motivated by the scale-space representation based method for blob detection with automatic scale selection (Lindeberg, 1998). Lindeberg proposes to detect blobs as scale-space extrema of a normalised Laplacian. Normalising is needed to keep magnitudes comparable across image scales. A normalised Laplacian at scale σ has the form $\sigma^2 L(x;\sigma)$, where $L(x;\sigma)$ is the Laplacian at scale σ.

Bright blobs, such as trees on the CHM, are found as scale-space minima of a normalised Laplacian. However, tree detection did not work well with automatic scale selection. Therefore, scale selection according to the predicted crown diameter was tried. The CHM was divided to height ranges of five meters (0-5 m etc.). In each height range, a centre value was used to predict corresponding tree crown diameter to get further crown radius in pixels. The scale σ was then obtained from the relation *crown radius* = 2σ. A normalised Laplacian was calculated from the CHM for each height range and the Laplacian images were combined into one image. Local minima found in the combined image were then considered as tree locations. The method is referred as Laplacian blob detection (LAP).

The described three methods are compared based on the accuracy of individual tree detection. For comparison, tree detection results are presented for local maxima finding on the unfiltered CHM (method **RAW**) and on the Gaussian filtered CHM at one scale that gave the most reasonable results (method **GAUS**). The scale σ was selected to be 0.8. To get results on individual tree basis, an estimated set of candidate tree locations was matched to a set of tree locations by field plot so that first 15 largest trees and candidates were searched for matches using a limit of 2.5 m difference in xy-direction and a limit of 4 m in height. The found matches were used to calculate average translations in x- and y-co-ordinates, translations were added to all tree candidate locations and the full sets were searched for matches. The matches were used to get second translations that were applied and full sets were searched for final matches. A program, originally made for matching start lists (Richmond, 2002), was modified to do the matching as described.

3. RESULTS

The accuracy of tree detection was not particularly good with any of the methods used (Table 1). Only about 40 % of all trees could be found. This was mainly caused by the large number of suppressed, small trees that were not detected from the CHM (Table 2). An example of the existence of suppressed trees on one field plot can be seen in Figure 1. However, larger trees were found with better success: about 60-70 % of dominant trees could be found (Table 2) and the basal area of the found trees was about 70 % of total basal area (Table 1).

About half of the trees could be found on the unfiltered CHM but the number of false positives was on unacceptable level. Height based filtering and the best fixed scale Gaussian filtering gave almost similar results. An example of tree locations produced by the height based filtering method on one field plot is presented in Figure 1. About 5 % more of the trees could be found by the maxima elimination method with the selected parameter values but the number of false positives was 2 % larger as well (Figure 2). More trees could be found by tuning values of the parameters but this increased the percentage of false positives at the same rate or faster. For example, if the maximality requirement *Tmax* was lowered to 6 and other parameter values were the selected ones (see Methods), percentages of found trees and non-tree candidates were 45.4 % and 13.3 %, respectively.

Laplacian blob detection could found as much of the trees as maxima elimination but the number of false positives was clearly larger (Figure 3). An interesting finding was that the blob detection method found more smaller trees than the other methods, including RAW that had the largest percentage of found trees (Table 2). The Laplacian filter responds to round form in shapes and thus a maximum is not necessarily needed to detect a blob. Therefore, the Laplacian blob detection found more partially suppressed trees than the other methods but it also found more extra locations, caused e.g. by large branches.

Method	Percentage of all trees		Basal area of found trees (%)
	Found trees	Non-tree candidates	
RAW	49.2	64.6	81.7
GAUS	36.7	6.6	68.0
HBF	37.0	5.9	67.6
ELIM	41.6	8.0	73.2
LAP	41.5	16.9	66.8

Table 1. Accuracy of the tree detection with different methods.

Method	Dominant trees (%)	Other (%)	Bias of height
RAW	79.4	7.4	-0.46
GAUS	61.4	2.4	-0.74
HBF	61.2	3.4	-0.79
ELIM	68.7	4.0	-0.73
LAP	62.4	12.5	-0.97

Table 2. Percentages of trees found for dominant and other trees and bias of height estimates of found trees.

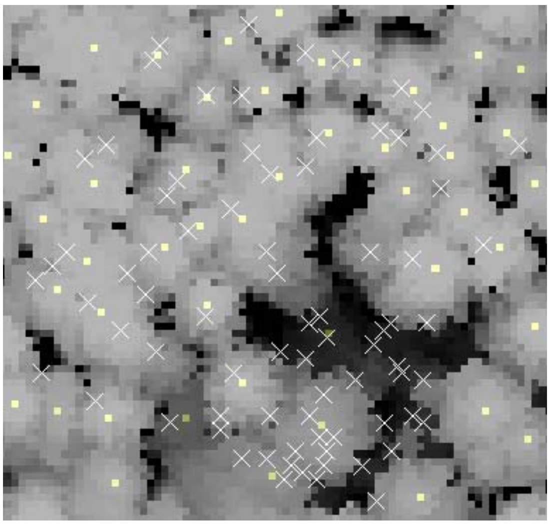

Figure 1. Tree locations produced by HBF method (filled squares) and field measured tree locations (x symbols) on one field plot.

The bias of height estimates of found trees in Table 2 is the average difference of the height estimates from the CHM and the field measured heights. The average difference is less than one meter although the bias includes the growth of trees between the measurement dates of the laser and field data. The larger bias of other methods compared to RAW is mainly caused by the filtering, which may move locations of local maxima slightly compared to the original image. This was not tried to correct for when height estimates were retrieved from the unfiltered CHM.

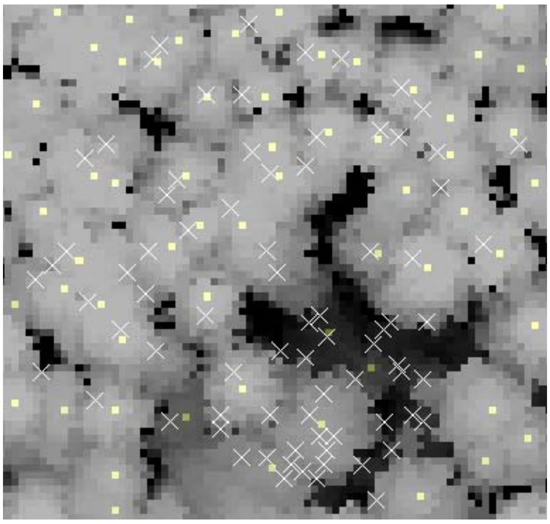

Figure 2. Tree locations produced by ELIM method.

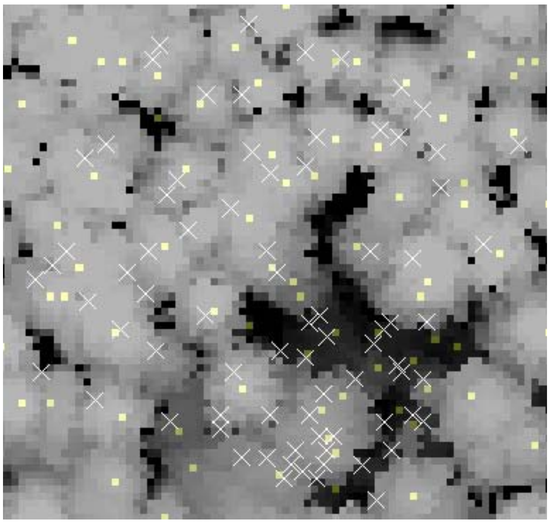

Figure 3. Tree locations produced by LAP method.

4. DISCUSSION

Three adaptive methods were presented for individual tree detection on a canopy height model derived from laser scanner data. The methods were tested using ten field plots located in mature, dense and often multi-layered forest stands. About 40 % of all trees and 70 % of dominant trees could be found so that the number of false positives was less than 10 %. More trees could be found on the unfiltered CHM but the percentage of non-tree maxima, 65 % of the number of the trees, proved the need for scale adjustment before tree detection.

For height based filtering, one have to choose the smallest and largest scale of the Gaussian filtering and other scales are interpolated linearly. One way for selection of the parameter scales is to check visually that the number of local maxima is reasonable at the low and high ends of the height range at a time. For maxima elimination and Laplacian blob detection methods, a crown width model is needed. This may be a problem because the relation of tree height and crown width is not so often modelled, probably due to lack of crown width measurements. However, it should be noted that high resolution laser scanner data is a potential source for crown width measurements even considering material for modelling. In this study, the original crown width model from other test site was adjusted by overlaying model results of the crown widths on the CHM and making visual examination. One problem of using crown width model as a parameter is the differences of tree species in tree height and crown width relation. Tree species is usually not yet known when a crown width model is applied in tree detection

The maxima elimination method gave the best results of tree detection with a reasonable number of false positives. However, this was achieved with the cost of including several parameters to keep the number of false positives low. When the maximality requirement was set lower to get more candidate locations on suppressed trees, the number of candidates on crown boundaries increased as well. Therefore, we should find some other criteria than maximality to place enough location candidates so that they avoid crown boundaries.

After height based filtering, only real local maxima are considered as tree locations. Thus for crown delineation, separation of tree crowns from each other can be done using normal methods that create segment for each local maxima. Some variant of watershed segmentation (Vincent and Soille, 1991) is often used. Maxima elimination and Laplacian blob detection methods can produce tree locations that are not local maxima and, correspondingly, all local maxima may not be accepted as tree locations. Therefore we have to use a segmentation method that creates segments for selected seed points only, such as marker based watershed segmentation. The segments of the tree locations that are not real local maxima can still be too small. The size of these can be increased if a scaled distance transform of the tree location points is subtracted from the CHM before segmentation.

If a larger proportion of trees should be found in this kind of dense, heavily stocked forest stands, besides further development of detection methods, one have to look at the laser data processing. A CHM is usually obtained as the difference of DSM and DTM. Because accurate retrieval of tree height has been the main interest, DSM has been created by taking the maximum height value of laser points within each raster element of DSM. Considering separability of trees, use of maximum value may reduce the valleys between tree crowns, making trees less distinguishable. However, it may be possible to make specific surface models for tree detection and segmentation.

References from Journals:

Hyyppä, J., Inkinen, M., 1999. Detecting and estimating attributes for single trees using laser scanner. *The Photogrammetric Journal of Finland*, 16(2), pp. 27-42.

Lindeberg, T., 1998. Feature detection with automatic scale selection. *International Journal of Computer Vision*, 30(2), pp.79-116.

Persson, Å., Holmgren, J., Söderman, U., 2002. Detecting and measuring individual trees using an airborne laser scanner.

Photogrammetric Engineering & Remote Sensing, 68, pp. 925-932.

Pitkänen, J., 2001. Individual tree detection in digital aerial images by combining locally adaptive binarization and local maximal methods. *Canadian Journal of Forest Research*, 31, pp. 832-844.

Popescu, S.C., Wynne, R.H., Nelson, R.F., 2002. Estimating plot-level tree heights with lidar: local filtering with a canopy-height based variable window size. *Computers and Electronics in Agriculture*, 37, pp. 71-95.

Vincent, L., Soille, P., 1991. Watersheds in digital spaces: an efficient algorithm based on immersion simulations. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 13, pp. 583-598.

References from Other Literature:
Hyyppä, J., Pyysalo, U., Hyyppä, H., Samberg, A., 2000. Elevation accuracy of laser scanning-derived digital terrain and target models in forest environment. Lidar Remote Sensing of Land and Sea, 4th EARSeL Workshop, Dresden, Germany, 16-17 June, 2000. 8 p.

References from websites:
Richmond, M., 2002. Match – a program for matching star lists. http://spiff.rit.edu/match (accessed 19 June 2002).