TREE CROWN DELINEATION FROM HIGH RESOLUTION AIRBORNE LIDAR BASED ON DENSITIES OF HIGH POINTS

M.Z.A. Rahman^{a, *}, B. G. H. Gorte^a

^a Delft Institute of Earth Observation and Space Systems (DEOS), Delft University of Technology, the Netherlands -(M.Z.AbdRahman, B.G.H.Gorte)@tudelft.nl

KEY WORDS: Tree detection, tree crown delineation, density of high points (DHP), canopy height model (CHM)

ABSTRACT:

Tree detection and tree crown delineation from Airborne LiDAR has been focusing mostly on utilizing the canopy height model (CHM). This paper presents a method for individual tree crown delineation based on densities of high points (DHP) from the high resolution Airborne LiDAR. The DHP method relies on the fact that the density of received laser pulses above a certain height is high at the centre of a tree crown and decreases towards the edge of the crown. In this study, the performance of this method is compared to the CHM approach. The results demonstrate that tree delineation based on DHP is at least comparable to the CHM approach. The DHP based approach performs better compared to the CHM especially for trees with almost flat-top crown shape. However, post-processing on tree crown segments is still necessary to improve the overall accuracy of tree detection and tree crown delineation.

1. INTRODUCTION

In most cases, tree detection and crown delineation are based on local maxima of the canopy height model (CHM) (Popescu et al. 2002, Brandtberg et al. 2003, Popescu et al. 2003, Kini 2004, Pitkanen et al. 2004, Weinacker et al. 2004, Falkowski et al. 2006). In addition, in most studies the Airborne LiDAR data were recorded during summer i.e. during leaf-on condition. In a previous study (Rahman and Gorte 2008b) we have shown that high density Airborne LiDAR provides good information on tree structure as well as undergrowth vegetation, especially in the leaf-off forest condition. Forest information derived at a detailed scale can be easily translated into coarser scales depending on the requirements of an application. For example, if the tree measurement is too detailed, it can be aggregated to mean values per stand or per hectare (Brandtberg et al. 2003).

Tree detection and crown delineation based on CHM has several disadvantages. Pitkanen, et al. (2004) developed adaptive methods for individual tree detection based on CHM derived from Airborne LiDAR data. The CHM in the first method was smoothed using a Gaussian filter and the degree of smoothing is defined by the heights of the pixels. Subsequently, the local maxima of the smoothed CHM were considered as tree locations. In the second method, an abundant number of possible tree locations was selected based on the local maxima or almost local maxima. The candidate pixels were then reduced based on 1) the slope within the assumed crown centre area and 2) the distance and valley depth between a location and its neighbouring locations. The second and third methods used a priori knowledge of the tree height and crown diameter relationship as a parameter to adapt with the tree size. It was pointed out that the results from these methods were not good since only 40% of the trees could be found and it was also reported that this was mainly caused by the large number of local maxima but the result also contained a huge number of false predictions. The results for fixed-scale Gaussian filtering and height-based Gaussian filtering were almost similar. The filtering process had slightly moved the predicted location of

Weinacker et al. (2004) reported that tree segmentation based on a smoothed CHM still contained a large number of wrong segments, in which the regions are too small to be a tree, have inappropriate crown shapes, or cover other trees and canopy gaps. The segments were refined based on their shapes and distance between tree tops. Brandtberg et al. (2003) used high density Airborne LiDAR data acquired during winter to detect and delineate individual trees. The tree crowns were delineated based on the scale-space theory in which the CHM was convolved with multi-scale Gaussian filters. The tree segmentation results were compared to the reference tree segments and it was shown that the segmentation approach had only detected and correctly delineated fewer than half of the trees in the study area. For this reason, Falkowski et al. (2006) introduced a new technique based on the spatial wavelet analysis (SWA) to automatically estimate the location, height and crown diameter of individual trees within mixed conifers using Airborne LiDAR. The advantage of this method is that no prior knowledge of the relationship between tree height and crown diameter is required. The performance of this method was comparable to the variable window filtering based on priori knowledge of the tree height and crown diameter relationship. Utilizing high density Airborne LiDAR Reitberger et al. (2007) introduced a method of tree detection based on stem detection using robust algorithm of RANSAC. The method works well on coniferous trees with a detection accuracy of 61%, but has a relatively low detection rate of 44% in deciduous forest. This

trees compared to the original image. However, for the method that is dependent on tree height and crown size relationship, the relation of tree height and crown width often is not modelled, probably due to a lack of crown measurements. Another disadvantage is caused by differences amongst tree species in the relation between tree heights and crown widths. This was also shown by Kini (2004) where the regression coefficients between crown size and tree height of deciduous, pines, and combined trees (deciduous and pines) were less than 0.6. This would decrease the performance of the tree detection and crown delineation process.

^{*} Corresponding author.

method seems quite promising in accompanying conventional ways of tree detection (i.e. based on CHM) especially when there is a relatively small amount of undergrowth vegetation under the dominant trees.

Recently we used the density of high points (DHP) from the high resolution Airborne LiDAR to detect individual tree locations (Rahman and Gorte 2008a). The LiDAR data was acquired during the winter season over a floodplain area in the Netherlands. The DHP based tree detection and crown delineation approach relies on the fact that the density of received laser pulses above a certain height is high at the centre of a tree crown and decreases towards the edge of the crown. The tree detection process was done on four datasets with different tree properties. It was shown that the DHP-based tree detection method could correctly detect more than 70% of the trees under different tree conditions.

The objective of this study is to compare the capability of the DHP with the CHM based approach for tree detection, as well as tree crown delineation. The comparison takes into account the following aspects:

- a. Capabilities of both approaches in detecting and delineating the trees
- b. Necessity of post-processing to improve the quality of tree locations and tree crown segments
- c. Differences in tree crown shapes, canopy gaps and undergrowth vegetation

The tree segmentation results are compared to manually delineated tree crown segments.

2. METHODOLOGY AND STUDY AREA

2.1 Study site description

The study site is in a forested area of the Duursche Waarden floodplain, the Netherlands (see Figure 1). The floodplain is situated along the IJssel River, the smallest distributary of the Rhine River in the Netherlands. The area is partly covered by meadow and arable land and a large part of the areas has become nature.

2.2 LiDAR data

The LiDAR data were captured using a FLI-MAP 400 system. The FLI-MAP 400 is a helicopter mounted LiDAR system designed to capture highly detailed terrain features with high accuracy. This system combines GPS positioning, rotating scanning laser and digital imagery in its data acquisition. It is claimed that the absolute accuracy of FLI-MAP 400 data measured over hard and level surfaces is 2.5 to 3.0 cm. The system is capable of scanning with oblique angle (both 7 degrees forward and 7 degrees back from nadir) and this increases the number of reflected pulses from the ground even in a quite densely vegetated area (Fugro SESL Geomatics Ltd 2009). The Airborne LiDAR of FLIMAP-400 data with a density of 70 points per meter square were acquired in 2007. In this study, three small sample areas were selected in which Dataset 1 covers about 1330 m² area, dataset 2 with 1024 m² and dataset 3 with 900 m² area (see Figure 1).



Figure 1. Study area at the Duursche Waarden floodplain, the Netherlands and the locations of sample datasets

These datasets differ in crown shape and density of undergrowth vegetation. Dataset 1 and Dataset 2 represent deciduous tree, while dataset 3 represents coniferous trees. Dataset 1 contains quite dense undergrowth vegetation (see Figure 2(a)), while the other two datasets (dataset 2 and 3) contain less undergrowth vegetation or an almost clear ground surface.



Figure 2. Three sample areas are selected from the study area, dataset 1 (a), dataset 2 (b) and dataset 3 (c)

2.3 Tree crown delineation procedure

2.3.1 DHP of tree crown: We have shown (Rahman and Gorte 2008a) for high density small footprint Airborne LiDAR that the density of laser pulses from tree branches above a certain reference height is highest at the centre of a tree crown and decreases towards the edge of crown (see Figure 3(c)). This is due to the fact that the total volume of tree branches is higher in the centre part of the tree crown and becomes less towards the edge of the crown (see Figures 3(a) and 3(b)). Furthermore it was shown (Rahman and Gorte 2008a) that regardless of crown shapes, this property remains unchanged. In the current study, we also show that besides detecting individual trees, the high point density properties can also be used for individual tree crown delineation.



Figure 3. Side view of a tree (a), aerial view of a tree (b) and the distribution of DHP for tree crowns (c)

In this study, the reference height is estimated automatically based on method used by Rahman and Gorte (2008b) for a single tree filtering from high density airborne LiDAR data (see Figure 4). The histogram is assumed to consist of 3 Gaussian functions representing tree crown, undergrowth vegetation and ground surface. The original histogram is filtered with a one-dimensional (1D) Gaussian filter to remove noise and to produce a smoother histogram shape. The first peak of the histogram is fitted with a Gaussian function and the reference height is defined as a 3σ from the mean value.



Figure 4. Reference level for group of trees

2.3.2 Tree crown delineation for DHP and CHM: Tree crown delineation for methods based on CHM and DHP were done using the Inverse Watershed segmentation algorithm (this algorithm will later refer to IW). The entire algorithm for tree crown delineation is as follows:

- 1. Create a histogram for the dataset and define the appropriate reference height
- 2. Select points above the reference height (see Figure 4)
- 3. Calculate the number of points in a column with a specified window size (point buffer) for each point in the dataset
- 4. *Convert the points to raster format with a specified spatial resolution (cell size). Each raster cell contains the highest value within that cell. In this study, the cell size is fixed to 0.3 meter
- 5. Normalize the cell value (number of high points) to weight that ranges from 0.1 to 1.0. The normalization is applied only on the DHP surface to reduce range of values for density
- 6. Apply 3x3 mean filter to the raster data
- 7. IW segmentation.
 - a. Start the tree crown segmentation from the pixel with the largest weight value
 - b. Grow the pixel to 8 neighbouring pixels and label these pixels if their values are lower than the seed pixel and more then zero. Stop the growing process if there is no other lower neighbouring pixels
 - c. Repeat steps 7a to 7b for the pixel with the next largest weight value

2.3.3 Post processing of tree crowns: The post-processing step aims at improving the tree crown segments. The process is based on four steps as follows:

- 1. Remove pixels that exceed a pre-defined maximum tree crown radius. Each tree location was assigned with a maximum tree crown radius and pixels that exceed this value are removed.
- Remove small tree crown segments. The minimum tree crown segment is calculated based on the minimum tree crown radius. The crown area is calculated based on a circular shape of a tree crown.
- 3. Re-classify pixels in steps (1) and (2) based on the following consideration.
 - a. Majority surrounding tree crown classes
 - b. The closest tree location
 - c. Maximum tree crown radius
- 4. Cavity filling process to fill holes inside the tree crown.

Dataset	Cell size (m)	*Point Buffer (m)	Min crown radius (m)	Maximum crown radius (m)	Reference level (m)
1	0.3	2.0	1.0	5.5	18.449
2	0.3	2.0	1.5	6.0	16.220
3	0.3	1.2	0.5	2.8	13.839

^{*} Only applies to the DHP based method

Table 1.Parameters for tree crown delineation based on DHP and CHM

Two parameters are required for the post-processing step namely the maximum and minimum radius of tree crowns. In this study, these are measured manually on the raw airborne LiDAR dataset. Finally, a cavity-filling process is used to remove holes inside a particular tree crown segment created by the zero-value (weight or elevation) pixels by assigning zerovalue pixels to the surrounding tree segments (see Figure 5).



Figure 5. Zero-value pixels (grey pixels) in (a) are assigned to their surrounding tree segment (each colour belongs to a particular tree crown segment) (b) and (c)

2.4 Evaluation

The evaluation step aims at comparing the results of tree detection and crown delineation of the DHP and CHM approaches to the reference tree location and tree crown segments. With the FLI-MAP 400 dataset we can separate each individual tree by manually observe the dataset. Therefore, the reference data are manually delineated from the airborne LiDAR data. There are 46 trees found in dataset 1, 24 trees in dataset 2 and 64 trees in dataset 3. The evaluation takes into account the capability of both methods to detect trees and delineate tree crown. The results are evaluated based on four aspects: 1) overall accuracy of tree detection, 2) omission and commission errors in tree detection, 3) overall accuracy, omission error and commission error is based on a conventional

^{*} For the CHM based crown delineation, the maximum height is used for point to raster conversion.

approach of error matrix assessment (Girard 2003). In addition, the evaluation is made on the performance of both approaches with and without post-processing of tree crown segments. The first step in the evaluation is to match the reconstructed tree crown segments with the reference crown segments. Both segments are considered matched if they have a maximum intersected area (see grey area in Figure 6, segment *a* is intersected with segment *b* and *c*. Segment *a* is matched with segment *c* since they have the largest intersected area compared to intersected area between segment *a* and *b*.). This information is used to estimate the overall accuracy. The other trees are labelled as un-matched segments and this information is used to calculate the omission and the commission errors.



Figure 6. Evaluation method

The overall accuracy, the omission error and the commission error for tree detection are quantified using equations (1)-(3).

 $\begin{array}{l} Overall \ Accuracy \ (tree \ detection) = 100 \ (N_m) \ / \ ((N_t - N_m) + (N_s \\ - \\ N_m) \ + \\ (1) \end{array}$

Omission error (tree detection) = $100 ((N_t - N_m) / N_t)$ (2)

Commission error (tree detection) = 100 ($(N_s - N_m) / N_s$), (3)

where N_m is a total number of matched tree polygons, N_t is a total number of reference trees, and N_s is a total number of reconstructed trees.

Equations (4)-(6) are used to quantify the overall accuracy, omission and commission errors of tree crown delineation.

Overall Accuracy (crown delineation) = 100 (T_i) / $((T_r - T_i) + (T_s - T_i) + T_i)$ (4)

Omission error (crown delineation) = 100 $((T_r - T_i) / T_r)$ (5)

Commission error (crown delineation) = $100 ((T_s - T_i) / T_s), (6)$

where T_i is a total intersected area of the matched tree polygons, T_r is a total area of the reference tree crowns, and T_s is a total area of the simulated tree crowns.

3. RESULTS AND DISCUSSIONS

3.1 Overall results for tree detection and crown delineation

In general, the overall accuracies of tree detection and tree crown delineation based on DHP for deciduous forest (dataset 1 and 2) are better than those for CHM (see Figure 7). However, for coniferous forest (dataset 3), the overall accuracy of tree detection and tree crown delineation based on CHM are slightly better than DHP. In general, the DHP based approach has successfully detected at least 60% of the trees with at least 45% accuracy in delineating the tree crowns. The CHM on the other hand has detected at least 51% of the trees and successfully delineates at least 30% of the tree crowns. Detailed explanation on the effect of post-processing, shape of tree crown and canopy gaps is discussed in the next sections.



Overall accuracy of tree crown delineation after the post-processing of tree crown (CHM)
Overall accuracy of tree crown delineation before the post-processing of tree crown (CHM)
Overall accuracy of tree crown delineation after the post-processing of tree crown (DHP)
Overall accuracy of tree crown delineation before the post-processing of tree crown (DHP)
Overall accuracy of tree detection after the post-processing of tree crown (CHM)
Overall accuracy of tree detection after the post-processing of tree crown (CHM)
Overall accuracy of tree detection before the post-processing of tree crown (CHM)
Overall accuracy of tree detection after the post-processing of tree crown (CHM)
Overall accuracy of tree detection after the post-processing of tree crown (CHM)

Overall accuracy of tree detection before the post-processing of tree crown (DHP)

Figure 7. Overall accuracy of tree detection and tree crown delineation

3.2 Effects of post-processing on tree crown segments

The results have shown that without the post-processing of tree crown segment, the tree detection based on DHP has better overall accuracy compared to CHM with the difference of 31% and 26% for dataset 1 and dataset 2 respectively (see Figure 7). The overall accuracy of tree detection based on CHM for dataset 3 is slightly better than DHP by 5%. On the other hand, tree crown delineation based on DHP has better accuracy compared to CHM by 21% and 16% for dataset 1 and dataset 2 respectively. However, the accuracy of tree crown delineation based on CHM is slightly higher compared to DHP by 7%. With the post-processing of tree crown segments the accuracy of tree detection has been improved quite significantly compared to the accuracy of tree crown delineation. As shown in Figure 8, the commission error has a dominant portion of the total errors of tree detection. This is caused by large number of wrong tree locations, especially produced by the CHM based approach. This error somehow tends to increase the commission error of tree crown delineation as depicted in Figure 9. The commission error of tree detection has been reduced quite significantly after the post-processing. The post-processing has increased the omission error of tree detection, especially for dataset 1 and dataset 2. However, this is still minor since the overall accuracy of tree detection increases after the post-processing.

3.3 Effects of different shapes of tree crown

The DHP approach produces more accurate results for deciduous trees (dataset 1 and dataset 2) in which trees in both datasets have an almost flat-top crown shape (see figures 2(a) and 2(b)).



Commission error of tree detection after the post processing of tree crown (CHM)
Commission error of tree detection before the post processing of tree crown (CHM)
Commission error of tree detection after the post processing of tree crown (DHP)
Commission error of tree detection before the post processing of tree crown (DHP)
Omission error of tree detection after the post processing of tree crown (CHM)
Omission error of tree detection before the post processing of tree crown (CHM)
Omission error of tree detection before the post processing of tree crown (CHM)
Omission error of tree detection after the post processing of tree crown (CHM)
Omission error of tree detection before the post processing of tree crown (DHP)
Omission error of tree detection before the post-processing of tree crown (DHP)
Figure 8. Omission and commission of tree detection



Commission error of tree crown delineation before the post processing of tree crown (CHM)
 Commission error of tree crown delineation after the post processing of tree crown (DHP)
 Commission error of tree crown delineation before the post processing of tree crown (DHP)
 Omission error of tree crown delineation after the post processing of tree crown (CHM)
 Omission error of tree crown delineation before the post processing of tree crown (CHM)
 Omission error of tree crown delineation after the post processing of tree crown (CHM)
 Omission error of tree crown delineation after the post processing of tree crown (DHP)
 Omission error of tree crown delineation before the post processing of tree crown (DHP)
 Omission error of tree crown delineation before the post processing of tree crown (DHP)
 Omission error of tree crown delineation before the post processing of tree crown (DHP)
 Omission error of tree crown delineation before the post processing of tree crown (DHP)
 Omission error of tree crown delineation before the post-processing of tree crown (DHP)
 Omission error of tree crown delineation before the post-processing of tree crown (DHP)

With this crown property, a single tree crown would exhibit multiple local maxima. Inevitably, this would reduce the capability of CHM approach to accurately detect the trees and it tends to create multiple segments for a single tree crown (see Figure 10). This problem becomes more serious for trees with a small crown gap (i.e. dataset 2). This is shown in dataset 2, where the accuracy of tree detection and crown delineation based on CHM is the lowest. As explained in section 2.3.1, compared to CHM the DHP approach would maintain its property regardless of tree crown shape. With this property the DHP surface might have a single tree location for a single tree crown (see Figure 10). Thus, the IW segmentation would easily grow from the centre of the crown towards the edge of tree crown. However, the DHP surfaces still contain irregularities that are caused by irregular distribution of DHP from the centre of tree crown to edge of crown.

The irregularities of the DHP surface may be caused by very dense undergrowth vegetation, as for example in dataset 1. Especially when the height of undergrowth vegetation is over the reference height it would create false signs of tree locations, so it is possible to get multiple tree crowns within a single tree. On the other hand, it is shown that the CHM based approach is slightly better compared to DHP for tree detection and crown delineation over coniferous trees. For this forest type, we may expect to get a single local maximum for a single tree crown. This should give an advantage compared to CHM based tree detection and tree crown delineation. However, the results of both methods do not show a significant difference. In this study, the low pass filter is used to reduce the irregularities on DHP and CHM surfaces, but this step affects the boundary of crown segments and the tree location shifted. Furthermore, the low pass filter suppresses small trees especially those located very near to larger trees.

4. CONCLUSION AND OUTLOOK

The results demonstrate that DHP based tree detection and tree crown delineation performs better than the CHM based approach. Only for coniferous trees the CHM based approach performs slightly better than the DHP approach. It is also shown that post-processing on tree crown segments is necessary especially for CHM based method to improve the overall accuracy of tree detection and tree crown delineation. It is proven that the crown shape would have a significant impact on tree delineation and by only relying on height information we might introduce a significant number of commission errors in both tree detection and tree crown delineation. In this study, separate evaluations have been made on tree detection and tree crown delineation. Since no algorithm can perfectly detect the trees and delineate the tree crowns, both assessments should be used together to describe the performance of tree delineation method. The results show that if one method is good in tree detection it does not necessarily good in tree crown delineation and vice versa. Therefore, it is crucial to find a method that has a good balance between tree detection and tree crown delineation. The overall framework of the individual tree delineation introduced in this study does not require any priori knowledge on tree height and crown diameter relationship. Thus the framework can be easily applied on different datasets. The datasets used in this study is rather small the ground surface is quite flat, thus the dataset are not normalized to the ground surface. However, for hilly area the normalization becomes necessary to get appropriate value for reference level. Future works is on going to combine the DHP based approach with a single tree filtering method introduced by Rahman and Gorte (2008b). This is a good combination since the product allows direct tree variable measurement from point clouds. In addition this method should be further tested on larger forest area which includes varieties of forest types and forest conditions.



0.0 Normalized density 1.0 1.57m Elevation 25.90m * Red line – tree crown segments by DHP or CHM

* Black line – reference tree crown segments

Figure 10. Results of tree crown delineation for DHP and CHM methods

REFERENCES

Brandtberg, T., Warner, T. A., Landenberger, R. E., and McGraw, J. B., 2003. Detection and analysis of individual leaf-

off tree crowns in small footprint, high sampling density lidar data from the eastern deciduous forest in North America. *Remote Sensing of Environment*, 85 (3), pp. 290-303.

Falkowski, M. J., Smith, A. M. S., Hudak, A. T., Gessler, P. E., Vierling, L. A., and Crookston, N. L., 2006. Automated estimation of individual conifer tree height and crown diameter via Two-dimensional spatial wavelet analysis of lidar data. *Canadian Journal of Remote Sensing*, 32 (2), pp. 153-161.

FUGRO SESL GEOMATICS Ltd., 2009, FLI-MAP 400. Available online at:

http://www.fugro.ca/services/asm/lidar01.htm (accessed 9 February 2009).

Girard, M. C., 2003. Processing of Remote Sensing Data, pp. 306-307 (London: Taylor & Francis).

Kini, A. U., 2004. TREEVAW: A versatile tool for analyzing forest canopy LiDAR data - A preview with an eye towards future. In *ASPRS images to decision: Remote Sensing foundation for GIS applications*, 12-16 September 2004, Kansas City, Mossouri (ASPRS).

Pitkanen, J., Maltamo, M., Hyyppa, J., and Yu, X., 2004. Adaptive methods for individual tree detection on airborne laser based canopy height model. In *ISPRS: Laser-scanners for forest and landscape assessment*, 3-6 October 2004, Freiburg, Germany (ISPRS), pp. 187-191.

Popescu, S. C., Wynne, R. H., and 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 (1-3), pp. 71-95.

Popescu, S. C., Wynne, R. H., and Nelson, R. F., 2003. Measuring individual tree crown diameter with lidar and assessing its influence on estimating forest volume and biomass. *Canadian Journal of Remote Sensing*, 29 (5), pp. 564–577.

Rahman, M. Z. A., and Gorte, B., 2008a. Individual tree detection based on densities of high points from high resolution airborne LiDAR. In *GEOBIA*, 2008 - Pixels, Objects, Intelligence: GEOgraphic Object Based Image Analysis for the 21st Century, 5 - 8 August 2008, Alberta, Canada (ISPRS), pp. 350-355.

Rahman, M. Z. A., and Gorte, B., 2008b. Tree filtering for high density Airborne LiDAR data. In *Silvilaser 2008: 8th international conference on LiDAR applications in forest assessment and inventory*, 17-19 September 2008, Edinburgh, UK, pp. 544-553.

Reitberger, J., Heurich, M., Krzystek, P., and Stilla, U., 2007. Single tree detection in forest areas with high-density LiDAR data. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 36, 139-144.

Weinacker, H., Koch, B., Heyder, U., and Weinacker, R., 2004. Development of filtering, segmentation and modeling modules for LiDAR and multispectral data as a fundament of an automatic forest inventory system. In *ISPRS: Laser-scanners for forest and landscape assessment*, 3-6 October 2004, Freiburg, Germany (ISPRS), pp. 50-55.