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AN OVERVIEW OF METHODS FOR TREE GEOMETRIC PARAMETER ESTIMATION FROM ALS DATA IN THE CONTEXT OF THEIR APPLICATION FOR AGRICULTURAL TREES

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Abstract. The aim of this paper is to overview and analyse existing methods for estimation of tree geometric parameters from Airborne Laser Scanning (ALS) data in the context of their possible application for agricultural areas. A detailed description of the estimation methodology proposed by various research groups is presented, including Canopy Height Model creation, tree identification, crown delineation in 2D and 3D, estimation of tree height, crown base height, crown diameters and crown volume. Efficiency and drawbacks of presented methods are identified. It is also analysed, whether the existing methods, originally developed for forestry areas, are suitable for agricultural trees.

Key words: ALS, trees, agriculture, remote sensing

INTRODUCTION

The rapid development of remote-sensing techniques began in the early 70s of the last century. The objective of those techniques is to collect Earth observations using non-contact techniques [Lillesand and Kiefer 1979]. Originally, this term refers to passive optical or radar sensors mounted on aerial platforms or satellites [Campbell 2002]. Currently there is a lot of active sensors available on the market (e.g. laser scanners), and some of them are mounted also on ground platforms. Remote sensing data are used for many different fields of science and economy, e.g. in environmental protection, geology, hydrology, agriculture, urban planning, meteorology.

One of the well documented areas of remote sensing application is forestry, for estimation of tree geometric parameter and forest biomass. Since 80s of the twentieth century

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laser and radar measurements were used for the inventory of forest areas [Nelson et al. 1984, 1988, Schreier et al. 1985, Maclean and Krabill 1986, Bernard et al. 1987, Currie et al. 1989, Hallikainen et al. 1989]. Since the mid-90s a large number of scientific studies showed a great potential of laser scanning data [Hyyppä et al. 1993, 1996, 1997, Kraus and Pfeifer 1998], that allows to reliably and accurately estimate important biophysical parameters of forest: tree height [Næsset 1997a], crown shape and dimensions [Means et al. 2000], crown base height [Vauhkonen 2010], crown volume [Hinsley et al. 2002], stem diameter [Popescu 2003], wood volume [Magnussen and Boudewyn 1998, Means et al. 2000, Næsset 1997b, Hyyppä and Hyyppä 1999] and other parameters related with the structure and the distribution of trees [Zimble et al. 2003, Maltamo et al. 2005]. First studies on the identification of individual trees appeared in the late 90s [Hyyppä and Inkinen 1999]. Initially, the studies involved only coniferous forests, while the first results for single tree recognition in deciduous forest appeared in [Brandtberg et al. 2003, Gaveau and Hill 2003]. With the appearance of robust methods for image processing, researchers started to classify tree species [Brandtberg et al. 2003, Holmgren and Persson 2004] and to measure the growth and crop of trees [Yu et al. 2004] by combining images with airborne laser scanning (ALS) data. As the years passed, the accuracy and the density of ALS data increased, allowing to precisely estimate parameters of forest areas and to use these parameters for forest planning and management of forest in many countries. It was proved by Dalponte et al. [2014b] that better results (in the sense of percent of correctly detected trees) can be obtained from ALS data analysis than from multispectral images of high resolution.

Monitoring of forest areas is of great importance for environmental protection and climate research [Yu et al. 2011], because trees are essential to maintain the proper carbon balance [Houghton et al. 2009]. Interest in biomass estimation is linked to forest health, photosynthetic activity and other processes related to the carbon cycle [Sexton et al. 2009]. For several years, there is a growing demand for continuous monitoring of forest condition [Houghton et al. 2009]. Currently, there are two main approaches related with estimation of the parameters of forest areas:

1. area based approach (ABA), typically providing data at stand level;
2. individual tree detection (ITD) approach where individual trees are of interest.

The procedure for data acquisition in ABA approach involves the use of ALS data and field plots, for which some tree classical measurements were performed. Parameter estimation is based on statistical relations between field measured values and predictor features obtained with remote sensing techniques [Means et al. 1999, Næsset 2002, Lim et al. 2003]. The results of ABA estimation are e.g. average tree height, average wood volume and number of trees in unit area. The unit area in ABA is usually a plot used to collect the measurements in the field. The results of plot analysis are presented in a grid format, which size depends on the size of train field, for which classical measurements were performed. The final results of stand-level forest inventory are obtained by weighted aggregation of the grid-level estimations inside the stand. The advantages of remote sensing of forest parameters compared to traditional stand-wise field inventory (SWFI) are: higher precision of estimated parameters [Holopainen et al. 2010], lower costs, fast results for large areas.

The ITD approach requires ALS data of high density, which increases the cost of data acquisition and storage. However, this approach allows to estimate tree geometric parameters with higher accuracy, which results in more reliable estimation of parameters of interest. Another advantage of ITD over ABA is a reduced demand of field measurements. The ITD approach started from manual interpretation of analogue aerial images [Gougeon and Moore 1988]. Later on, a lot of research were performed on single tree identification based on large scale aerial photos or high-spatial resolution remotely sensed imagery. The main challenge was to automate the single tree identification process, by applying various identification algorithms [Erikson and Olofsson 2005]. The main methods used for extraction of individual trees from photos or images are: local maxima detection [Dralle and Rudemo 1996], local maxima filtering with fixed or variable window sizes [Wulder et al. 2002, Pouliot et al. 2002], valley-following [Gougeon 1995], edge detection using scale-space theory [Brandtberg and Walter 1998], template-matching [Pollock 1996], local transect analysis [Pouliot et al. 2002], watershed segmentation [Wang et al. 2004]. The effectiveness of algorithms relies directly on the characteristics of study area (canopy spectral properties, canopy structure complexity), quality of data and weather conditions during data acquisition (images of large exposition may saturate values of biophysical parameters and shadows impede object detection).

Still various research groups are attempting to characterize forest inventory parameters with ABA or ITD approaches [Angelo et al. 2010, Holmgren et al. 2012, Dupuy et al. 2013, Longuetaud et al 2013, Grafström and Ringvall 2013]. Vastaranta et al. [2012] proposed to use ITD results to improve ABA analysis. It is important to note, that trees are not anthropogenic objects so their geometry is very complex: without straight and perpendicular lines, different tree species have different crown morphologies and even the crown structure of a single species vary depending on local conditions [Heurich 2008]. Tree crowns vary significantly in form and size, often the crowns of adjacent trees form a single common crown with a fuzzy boundary between trees. On the other hand single tree may form broad or layered crown and even multitrunk trees exist. For these reasons, each tree should be considered as a unique object, and many unusual cases cannot be recognized correctly from two-dimensional imagery. Some identification problems can be overcome with ALS data. Because the direct three-dimensional measurement of canopy coordinates is possible, so the geometrical, rather than spectral analysis are performed [Chen et al. 2006, Véga et al. 2014].

Some comparison of ALS based methods for single tree identification in various conditions can be found in [Kaartinen and Hyyppä 2008, Vauhkonen et al. 2012, Kaartinen et al. 2012]. Although ALS point cloud is a source data, tree identification is performed usually on the ALS based raster product – Canopy Height Model (CHM). It was proved by Kaartinen and Hyyppä [2008] that the choice of the method for single tree identification affects the final accuracy of tree location and height determination and consequently, overall quality of inventory. It was also noticed in [Kaartinen et al. 2012] that methods based only on height analysis (CHM) are not suitable to identify suppressed trees. In this case analysis on discrete ALS points or full-waveform data are of great potential, as presented in [Reitberger et al. 2009, Wang et al. 2008, Gupta et al. 2010a]. The performance of algorithms to identify single trees from ALS data depends mainly on forest stand characteristics [Falkowski et al. 2008, Kaartinen et al. 2008], however spatial resolution of remote sensing data is also of importance [Wulder et al. 2000, 2002, Tesfamichael et al. 2009].

The aim of this paper is to overview and analyse methods for single tree identification, crown delineation and estimation of tree geometric parameters based on ALS data. It will be also analysed, whether the existing methods, originally developed for forestry areas, are suitable for agricultural trees. Agricultural trees are considered here as trees that are valuable in agriculture due to fruit production, e.g. orange trees, olive trees, apple trees.

TREE DETECTION

The procedure of individual tree detection is generally composed of two stages: creating canopy height model (CHM) from ALS data and searching for local maxima of CHM assumed to be treetops. There is a number of various methods and strategies applied for both stages, and many factors influencing the quality of results were taken into account by researchers to obtain the optimum solution. Details are presented in following subsections.

CREATING CHM

Canopy height model represents a rough surface of the canopy. It is calculated by subtracting the height value of the digital terrain model (DTM) at each pixel from the height value of digital surface model (DSM), so the CHM heights are the relative heights (or normalized heights) above the ground. The quality of CHM depends directly on the quality and spatial resolution of both DTM and DSM.

A common strategy to create a CHM raster from discrete, normalized ALS points is the minimum curvature method [Smith and Wessel 1990], applied e.g. in [Solberg et al. 2006, Kaartinen and Hyyppä 2008]. The typical approach is to use the first pulse return from ALS data and to create a CHM as a raster. With this method, the CMH surface is obtained iteratively, starting from a plane, and then iteratively smoothed closer and closer to fit the data. The characteristic of this method is that the created surface does not cover the source points and allows the surface to extend upwards over the uppermost points over a tree top.

In literature, another methods of CHM creation can also be found. Gupta et al. [2010a] implemented active surface algorithm – a physically-based deformable model, to deform the surface of raw CHM model by topological constraints. They used trial and error approach to tune the final results. Persson et al. [2002] proposed to use active contour algorithms (also called “snakes”) that is widely used in image processing for delineating object outline from a noisy image. In this way they were able to remove points that were not reflected from trees.

SEARCHING FOR TREETOPS

Treetops are identified as local maxima on CHM. Local maxima on the raster is usually considered as a pixel that is surrounded by 8 pixels of smaller height than itself. To remove the noise from the raster, a low-pass smoothing filter is applied. Usually a Gauss filter is used in forest studies. After the filter is applied, treetops can be identified and they become seed points for further processing, e.g. for tree crown delineation algorithms [Morsdorf et al. 2003]. An alternative method for tree tops identification was presented in [Yu et al. 2011]. For CHM raster that was previously smoothed with a Gauss filter, minimum curvatures were calculated. Pixels of higher minimum curvature than neighbouring pixels were assumed to be treetops.

It is necessary to define several parameters for the smoothing filter, one of them is a window size in which the smoothing is performed. Too small window size results in commission errors, when local treetops of the same tree are classified as separate objects, so more trees are identified. On the other hand, large window size results in omission errors, that is, some trees are not identified [Zhao and Popescu 2007]. The size of the window should depend on a CHM resolution and expected tree crown diameters. While the resolution of the CMH usually depend on the ALS data, crown diameters are not known unless some field measurements are performed or some expert knowledge on forest stand characteristics is provided. A correct definition of the window size is particularly important for suppressed or concentrated trees [Morsdorf et al. 2003]. The most common parameter is 3×3 squared window, however 5×5 and 7×7 windows were also used.

Another parameters that needs to be defined for the Gaussian filter is the number of iterations, that affects the intensity of raster smoothing. Solberg et al. [2006] investigated an optimum number of smoothing iterations by applying Gaussian low-pass filter 1, 3, 5 or 7 times with a window size of 3×3 pixels. It was found, that the best results were obtained when the filter was applied 3 times, taking into account the number of correctly identified trees and the distance of identified seed points from measured treetops. It was noticed by the authors, that setting the degree of smoothing of the CHM represents a crucial balance between two criteria of success, i.e., omission and commission. A mild smoothing results in a high fraction of identified trees but it leaves too many "false" trees, while rough smoothing leaves a high fraction of unidentified trees without "false" trees. The number of iterations may also be defined by the expected level of filter smoothing, measured as a standard deviation σ of the Gaussian distribution. In [Persson et al. 2002] various setting of σ was applied: $4/\pi$, $6/\pi$ and $8/\pi$. The best results were obtained for $\sigma = 4/\pi$, so that the most trees were detected but also some large trees had more than one maximum. Another Gaussian scaling was proposed in [Koch et al. 2006]. First, the CHM was divided into two classes with a threshold at the height of 20 m. For each class different sigma was applied and the results were merged after the identification was performed separately in each class. The best results were obtained with $\sigma = 0.81$ for small trees and $\sigma = 2.0$ for large trees. Pitkänen et al. [2004] showed that σ of the Gaussian filtering should be adjusted visually before tree selection. It means that not only a window size and weights influence the results, but also a number of smoothing iterations should be tuned to each study area.

An interesting approach to identify trees was proposed in [Hyyppä et al. 2012]. In addition to classical CHM, authors created also 3 surfaces from the last pulse returns, representing minimum, mean and maximum height of a last pulse in a pixel. The idea was to use the canopy penetration capability of the last pulse returns to identify overlapping trees. The authors stated that the last pulse is more sensitive to lower canopy levels and a significant drop (at least 2 m) in the last pulse elevation can be found for overlapping trees. An improvement of several percent was obtained when minimum last pulse height surface was used intead of CHM obtained with the first pulse. The improvement increased with the increasing density of the forest stand and decreasing diameter breast height. The disadvantage of this approach is the large number of commission errors, caused by the gaps within individual tree crowns.

Finally, it was proposed by Gupta et al. [2010a] not to apply a Gaussian smoothing filter, but to filter out incorrect local maxima based on threshold distance. The threshold distance is a forest dependent parameter. It should be defined according to forest conditions and tree species. For trees having wider canopies, the distance should be large, between 4 to 6 m, because local maxima from smaller peaks most likely represent branches of the same tree. For small canopies a distance of 2 to 4 m was recommended by the authors.

Table 1 presents the comparison of selected features of treetop identification strategies, that were applied by various research groups cited above. One can see that a 3x3 Gaussian smoothing was the most common filtration method, but the definition of times that the filter was run varies. Finally, usually a single layer CHM model was created, while the two-layers model (splicing CHM at a defined height and analyse both layers separately) was recommended in studies that concerned trees of significantly varying heights.

Table 1. Comparison of tree detection strategies

Author	Filtration method	Filter runs	CHM creation method	CHM division
Hyyppä et al. 2001	Gauss 3x3	N/A	N/A	none
Morsdorf et al. 2003	Gauss 3x3	N/A	N/A	none
Persson et al. 2002	Gauss 3x3	$\sigma = 4/\pi, 6/\pi, 8/\pi$	ACA	none
Koch et al. 2006	Gauss 3x3	$\sigma = 0.81$, $\sigma = 2.0$	N/A	2 (0–20 m, >20 m)
Gupta et al. 2010a	threshold distance	–	ASA	2 (wide & small crowns)
Solberg et al. 2006	Gauss 3x3	3	MC	none
Kaartinen and Hyyppä 2008	Gauss 3x3	3	MC	none
Yu et al. 2011	Gauss 3x3	σ	N/A	none
Hyyppä et al. 2012	Gauss 3x3	N/A	N/A, last return	none

N/A – information not available, ACA – active contour algorithm, ASA – active surface algorithm, MC – minimum curvature algorithm

TREE CROWN SHAPE

After the treetop are identified, as described in the previous section, tree crown shape can be retrieved with a two-dimensional contour, as a crown shape projection to (x,y) plane. This step is called in the literature as tree crown delineation and is usually based on CMH processing. Alternatively, for dense ALS data, it is possible to present the crown shape in 3D.

2-DIMENSIONAL APPROACH

Region growing algorithm

One of the most popular methods for tree crown delineation is a region growing algorithm, used e.g. in [Hyyppä et al. 2001, Solberg et al. 2006, Kaartinen and Hyyppä 2008]. The algorithm was originally designed for an image segmentation, so it operates on the CHM raster. The algorithm starts from the grid points containing identified treetops – these pixels become the seed pixels for the segments. The algorithm runs iteratively, until the final segments are defined, that is when there is no change between two iterations or all CHM pixels already belong to a segment. In each iteration, pixels are joined to an existing segment if 2 conditions are met: 1) the pixel is a neighbour (in x, y or diagonal direction) to any pixel inside the segment, 2) the joined pixel height is lower than the height of the neighbouring point inside the segment. In this way the regions are gradually extending downwards and outwards in the CHM.

Several modifications of region growing algorithm impose additional conditions for joining the points e.g. a pixel will be joined to the segment only if the vertical slope between the pixel and the neighbouring pixel inside the segment is the steepest slope between the pixel and any neighbouring pixel. Additionally, a star shape restriction is often included to avoid strange object shapes; accepted are star shape object, in which any point inside the shape is "visible" directly from the seed point. The star shape restriction was used e.g. by Solberg et al. [2006] and Kaartinen and Hyyppä [2008]. Finally, in case a pixel can be joined to more than one segment, it is connected to the segment for which the distance to the seed point is the smallest.

The classical growing region algorithm, in which a segment by segment processing is performed, is sensitive to seed point location and the order of segment processing, particularly when object edges are not clear e.g. for overlaying trees. Therefore a simultaneous region growing technique have been developed, in which all regions are allowed to grow at the same time. This approach is computationally less effective, which may become a limitation in case of processing some big areas.

A comparative analysis of several region growing algorithm modifications can be found in [Hyyppä et al. 2001]. Authors run the algorithms on the same test area and found, that methods using region growing algorithm allowed to correctly segment up to 50% of crowns, while 45% of crowns were merged, 4% of crowns were split and 1% was not segmented at all.

Watershed transformation

The idea of watershed transformation was introduce in [Beucher and Lantuejoul 1979]. This approach consists of placing a water source in each regional minima of the relief to flood the entire area from the source and to build barriers when different water source meet. In other words, the watershed of a relief corresponds to the limits of the basins of the water drops. This method is now a well-established method for image segmentation [Meyer and Beucher 1990]. For crown diameter delineation a watershed segmentation is performed on the negative CHM with low elevation points filtered out [Zhao and Popescu 2007, Kwak et. al. 2010, Sambugaro et al. 2013], called the segmentation function.

The typical problem of classical watershed transformation is the over-segmentation problem. Therefore Soille [2003] introduced a marker-controlled watershed segmentation, in which local maxima of the input image are replaced by the set of user defined markers, called marker function. The segmentation algorithm ensures a 1:1 relationship between the markers and resulting segments, so the segmentation success depends on how accurately the object markers represent the objects [Ene et al. 2012]. Appropriate definition of marker and segmentation functions for marker-controlled watershed segmentation resulted in delineated boundaries of individual crowns [Wang et al. 2004]. Schardt et al. [2002] proved, that this method can be applied also for deciduous tree species, despite their complex canopy structure, only if appropriate marker and segmentation functions are generated from ALS data.

Another modification was proposed by Ene et al. [2012]. Authors applied adaptive low-pass filtering for regional maxima to reduce the number of segments. They used the extended maxim transform [Soille 2003] to filter out regional maxima with values below a defined height threshold. The value of this height threshold can be obtained empirically (as suggested by Chen et al. [2006] and Kwak et al. [2007]), or directly from CHM analysis. In the latter case, Dalponte et al. [2014b] suggested to calculate CHM height residuals from locally smoothed CHM and set the height threshold as a 25th percentile obtained from the distribution of absolute residuals.

It was found by Yu et al. [2011] that the marker-controlled watershed segmentation performs better for large trees and the percentage of detected crown contours decreases in dense forests. In [Ene et al. 2012] different results were obtained for top, middle and bottom layers of forest. In [Dalponte et al. 2014a] it was shown that the results very depending on tree species. The efficiency of watershed transformation found in various studies is 51–69% for coniferous trees and 40% for deciduous trees.

Pouring algorithm

The pouring algorithm resembles water being poured onto mountains, thus being similar to an inverted, classical watershed-algorithm. Starting from the seed points, regions are extended by pixels of lower or equal height to the neighbouring pixel that belongs to the segment [Koch et al. 2006]. This step produces a first approximation of the crown shapes, with many very small and many vary large regions. The small ones are joined to larger segments, usually based on the distance criteria. Then all segments are tested for being a single tree or a group of trees by fitting an ellipse to the segment. A segment is considered as a group, if the ellipse diameter ratio exceeds 2.5 and the segment area is at least 3 times larger than the defined minimal tree crown area. The congregations are disjoined following the approach developed by Straub and Heipke [2001] for tree groups within settlements. The biggest inner circle in the segment is detected and subtracted from the segment iteratively, until the segments area is below the double minimal tree crown area. Then the circular segments are expanded until regions touch each other, touch original border or until the height difference between new and old border do not exceed 60 cm. Finally the tree areas can be reduced based on the minimum slope threshold between the treetop and border point, as proposed by Friedlaender [2002]. It is typical for pouring algorithm that crown areas are overestimated, and the performance for coniferous trees (<87% of detected tree crowns) is much better than for deciduous trees (<62%).

3-DIMENTIONAL APPROACH

Voxel space

Transition into voxel space means that the 3-dimensional study space is divided into rows, columns and layers, an then the normalized ALS point cloud is portioned into regular boxes called voxels, representing a fragment of real world space. ALS points inside each voxel are resampled, so that each voxel is represented by the number of ALS points inside. In this way voxels from the same layer can be recognized as a raster, representing the ALS density. The idea of tree crown determination presented by Wang et al. [2008] is based on the analysis of voxel layers, starting from the top to the bottom layer. For the top layers, high density of ALS data corresponds to the tree crown, while the process becomes more complicated for middle and bottom layers, where tree crown may overlap each other. The top layer contours are treated as reference regions and seed points are the voxels of the highest ALS density. Then a hierarchical morphological opening and closing process with a group of structuring elements is performed. Voxels of lower ALS density are included into structures iteratively. For middle and bottom layers, another morphological algorithm was proposed to stop the structures growing: the reference regions are dilated by a defined radius and the structure enlargement is stopped when the structures touch each other. Some improvement of voxel space approach was proposed by Vauhkonen et al. [2012], who supplement the approach with tree crown merging algorithm, based on the relations between horizontal distance between treetops, their height difference, crown base height difference and crown radius.

The defect of this approach is that if a tree is not recognized in the top layers e.g. because it is a low tree, it will probably not be detected as separated tree but included into one of the nearby tree. It was also noticed, that for wide trees, the process resulted in crown split. The results are also sensitive to voxel dimensions – small horizontal dimension of voxels improves the accuracy but is more prone to crown splits, thick layers improve the delineation of deciduous trees but limit the 3D representation. It was proposed by Wang et al. [2008] that the approach may be improved if voxel space is not uniform and growing structure limiting radius varies between layers. It was noticed, that the method performs better for old trees (>80% of detected tree crowns) than for younger trees (55–75%).

k-means approach

k-means algorithm aims to minimize the total intra-cluster variance or the squared error. In the contrary to previously described methods, it operates directly on ALS point cloud to minimize the sum of distances between each point and its closest centroid of existing cluster [Gupta et al. 2010a]. After the ALS point cloud is clustered, each cluster is reconstructed with convex hull approach [Barber et al. 1996] into 3D convex polotype that consists of triangular surfaces. The convex hull algorithm returns a set of points, that create the smallest convex containing all points in the cluster. Therefore, the 3D convex polotype can be considered as a 3D representation of tree crown [Kwak et al. 2010]. The algorithm requires a dense ALS point cloud to outputs reliable results, so due to its computational complexity big regions cannot be processed efficiently with current computational capabilities.

Because k-means algorithm is based on Euclidian distance, it tends to create ball shaped clusters, as presented by Lindberg et al. [2013]. At the same time, for coniferous tree the height of a crown is usually several times larger than the diameter of this crown [Morsdorf et al. 2003]. For this reason, k-means is performed on the Z-scaled CHM to transform tall tree crowns into ball objects. After the k-means algorithm is performed, the height value of the clustered data are scaled-up to its original. It was shown in Gupta et al. [2010b] that scaling down the height value improves the results of tree crown delineation. The downscaling factor is usually based on tree species, field measurement or visual inspection of the results. There is no universal scaling factor value or automatic method for its adjusting, which is a serious drawback of this approach.

In the classical *k*-means approach, the algorithm creates *k* clusters without initial information on cluster centre location. In Morsdorf et al. [2003] a modified k-means approach was proposed, in which the cluster seed points were defined by the treetops detected from CHM. Gupta et al. [2010b] compared the classical and modified *k*-means, and noticed that the modified approach outperforms the classical one.

Kandare et al. [2014] proposed k-means clustering separately on the vertical layers with a user-defined distance. Then the clusters are aggregated based on the spatial relations and separated into two cluster based on Kernel density function. The clusters are merged along vertical direction, following the rule, that two cluster are merged if their horizontal projections are overlapping polygons for more than 10%. Finally, the convex hull is performed, to create a tree crown shape from merged clusters.

TREE GEOMETRIC PARAMETERS

After the tree crown is delineated, points that correspond to individual tree can be extracted from ALS point cloud. Than some tree geometric parameters can be estimated from points in the object, namely tree height, crown base height, crown diameters and crown volume. The idea of tree geometric parameter estimation from ALS data is presented in Figure 1. These parameters are useful e.g. for stem volume estimation [Maltamo et al. 2006, Villikka et al. 2008, Allouis et al. 2013], tree biomass estimation [Persson et al. 2002, Vaglio Laurin et al. 2014] and breast height diameter [Kalliovirta and Tokola 2005].

TREE HEIGHT

The most straightforward approach to estimate tree height is to use the height of the highest point belonging to the segment [Morsdorf et al. 2003, Solberg et al. 2006] or use the height of the top voxel in case of voxel transition [Wang et al. 2008]. Persson et al. [2002] investigated, whether the size of laser beam influence the results. He found, that although small laser beams are more suitable for dense forests, they do not affect tree height estimates (RMSE = 0.63 m and correlation coefficient between estimated and measured values was 0.99). If some field measurements of tree height are available in the study area, a normal linear regression model can be derived and applied to estimate tree heights for other trees [Morsdorf et al. 2003, Heurich 2008].

CROWN BASE HEIGHT

The classical approach to estimate crown base height is to filter out ALS points belonging to the ground and low vegetation and then to use the height of the lowest point. The difference between the highest and the lowest point in the object is called crown depth, and crown base height calculated as a difference of tree height and crown depth is called crown insertion [Kaartinen and Hyyppä 2008].

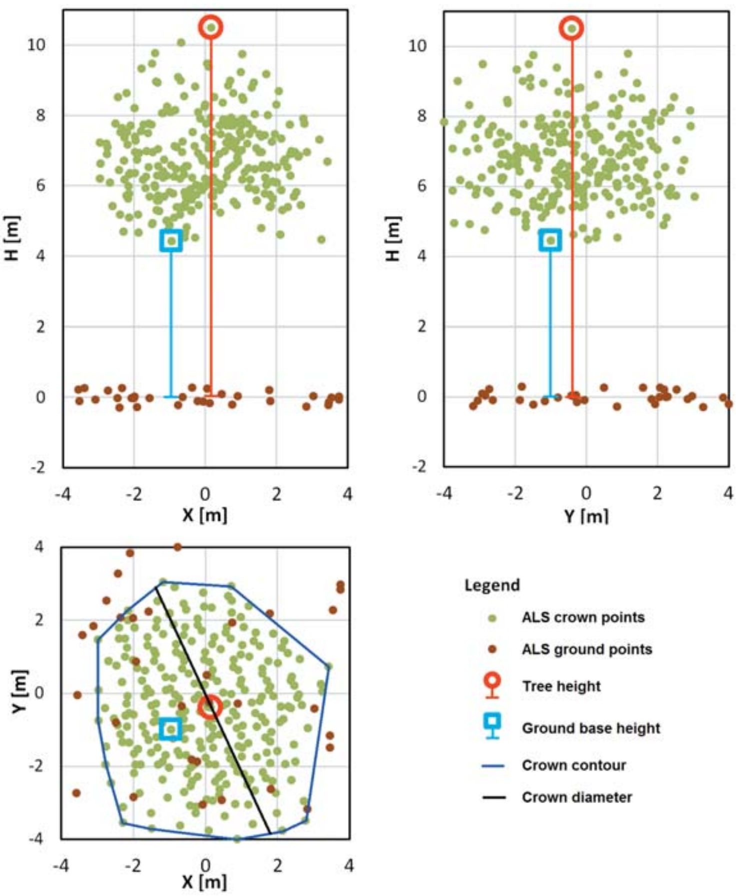

Fig. 1. The idea of tree geometric parameter estimation

Another approach is to use all points in the object and estimate crown base height as the height of a point, for which there is a biggest height difference to a neighbouring point below [Solberg et al. 2006]. Similar approach was proposed by Kaartinen and Hyyppä [2008]. A point cloud of first and fourth echoes was used to calculate deciles (eleven values that divide the sorted data into ten equal parts) of the z value and differences between adjacent deciles. The crown base height was defined as the decile which had the largest difference below itself, when excluding the uppermost two deciles.

CROWN DIAMETER

The crown diameter is usually estimated directly from the crown shape as the average of two values measured along two perpendicular directions from the location of the tree top to crown border [Kaartinen and Hyyppä 2008]. It can also be computed as a doubled mean value of four crown radii taken from the treetop in the cardinal directions [Solberg et al. 2006]. Alternatively, crown diameter can be estimated based on the empirical relation between tree height and crown diameter for trees of a certain species [Popescu et al. 2003]. It can also be derived from a regression model build on the basis of field measurements and selected tree geometric parameters, including tree height [Kaartinen and Hyyppä 2008].

CROWN VOLUME

For 3D approach crown volume is directly estimated as convex hull volume [Morsdorf et al. 2003] or voxel volume [Wang et al. 2008]. If 2D approach was applied for crown delineation, crown volume can be calculated as the volume between the CHM and crown base height for each object. In this case crown area (calculated as the area of crown shape polygon) is multiplied by the corresponding crown depth [Kaartinen and Hyyppä 2008]. Kato et al. [2009] estimated crown volume with a regression model and wrapped surface.

RANDOM FORESTS

Although tree geometric parameters can be estimated independently or consecutively, they can also be estimated simultaneously using random forest algorithm [Breiman 2001] – a nonparametric regression approach, well-known in computer machine learning tasks. A random forest is composed of a set of decision trees build on the basis on training data. Each decision tree is a set of rules that split the feature space, thus creating multi-level regression model. The decision trees are built in a way that ensures maximum randomness – samples from training dataset as well as features at each node of decision tree are selected randomly. A part of training data that was not used to build any decision tree (usually set to 20% of all samples) is used to predict the accuracy of random forest estimates [Yu et al. 2011]. After the random forest is created, ALS point cloud can be classified with random forest – it is classified to the class, for which it was classified most often by all decision trees. Random forest application for tree geometric parameters estimation was presented e.g. in Yu et al. [2011] and Heurich [2008]. Forzieri et al. [2009] proposed a simplified approach, in which a multi attribute decision making is created during a calibration phase, that is based on field measurements.

QUALITY OF THE RESULTS

The accuracy of estimated parameters reported in selected papers is presented in Table 2. Although Table 2 presents studies performed with different methods and for different areas, it gives a rough vision about the quality of results. Moreover, various quality indicators are provided in papers, among which the RMSE is the most frequent one.

Table 2. Accuracy of tree geometric parameters estimated from ALS data reported in selected studies

	Tree location	Tree height	Crown base height	Crown diameters
Morsdorf et al. 2003	Mean = 1.12 m Std = 0.64 m	RMSE = 0.60 m		
Solberg et al. 2006		RMSE = 1.2 m	RMSE = 3.5 m	RMSE = 1.1 m
Persson et al. 2002		RMSE = 0.63 m	RMSE = 0.61 m	
Heurich 2008	Mean = 0.54 m Std = 1.44 m			Mean = 0.25 m StdDev = 1.02 m
Kaartinen and Hyyppa 2008	Mean: 0.6–1.4 m Std: 0.5–1.3 m	RMSE: 0.6–4.6 m	RMSE: 5.4–9.0 m	relative error < 45%
Kato et al. 2009		$RMSE_C$ = 1.56 m $RMSE_D$ = 1.41 m	$RMSE_C$ = 1.62 m $RMSE_D$ = 1.54 m	$RMSE_C$ = 0.75 m $RMSE_D$ = 2.89 m
Popescu et al. 2003		$RMSE_C$ = 0.68 m $RMSE_D$ = 0.70 m		$RMSE_C$ = 1.36 m $RMSE_D$ = 1.41 m

Std – standard deviation, RMSE – root mean square, C – coniferous, D – deciduous

Detected tree location with respect to field measurements differs on average between 0.5 to 1.4 m with standard deviation between 0.5 up to 1.44 m. Tree location is usually used as a seed point for crown delineation, therefore as long as the crown are wide enough, this accuracy seems to be sufficient. RMSE of tree height varies from 0.60 to 4.6 m (majority of research provided RMSE < 1.6 m), and small differences in results are reported between coniferous and deciduous trees. It is also reported in majority of studies, that tree heights are underestimated. This in in the contrast with crown base heights that are usually overestimated with RMSE varying from 0.61 to 9.0 m. Crown diameters are estimated with RMSE between 0.75 to 2.89 m, and the results are less accurate for deciduous trees than for conifers. Because crown diameter estimates are directly related with tree contour, crown delineation strategy should be chosen carefully.

APPLICATION FOR AGRICULTURE

The knowledge on tree geometric parameters supports efficient management and agricultural production [Doruska and Burkhart 1994]. It allows to predict harvest, to plan dosage of fertilizers, to manage irrigation and pruning actions [Estornell et al. 2014]. However, it should be noted that the structure of agricultural trees is different that the structure of forest trees, because agricultural trees usually have short stem and biomass is concentrated in the crown [Berg et al. 1997]. There are no allometric equation that relate certain parameters like volume or biomass with typical measurements taken in the field. For this reason, it should be investigated, whether the existing methods, originally developed for forestry areas, are suitable for agricultural trees.

So far, only several studies were performed on estimation of tree geometric parameters for individual agricultural trees. Usually researchers concentrated on ABA method, in which ALS data was supported with high-resolution aerial photos. Recio et al. [2013] proposed a plot-based approach to detect fruit trees and extract tree and plot-based parameters e.g. fraction of tree cover, planting patters, number of trees. The method was based on k-means algorithm followed by the automatic detection of the classes representing trees. Recio et al. [2012] presented a method for automated extraction of agronomic parameters, suitable for agricultural management, inventory and irrigation planning at plot level. The processing is based on k-means classification of Normalized Difference Vegetation Index [NVDI, Rouse et al. 1973] image. Multispectral images analysis can also be combined with ALS data to automatic NDVI calculation for individual trees in an apple orchard using growing regions algorithm from identified treetop and analysing the pixels inside the crown border [Viau et al. 2005].

Estornell et al. [2014] showed ABA for tree height and biomass estimation of olive trees, using sparse ALS data (0.5 pt m^{-2}). They performed biomass measurements for selected trees in the field, following the strategy proposed by Velázquez-Marti et al. [2012]. Then they used FUSION software to estimate plot parameters: maximum height, mean, standard deviation, coefficient of variation, kurtosis, skewness, interquartile distance, percentile values (5th, 20th, 40th, 50th, 60th, 80th, 95th) and ALS point distribution on selected horizontal layers (0.5–1.5 m, 1.5–2.5 m, 2.5–3.5 m, 3.5–4.5 m). They created a regression model explaining 70% of variability of estimated parameters.

In Fieber et al. [2013] authors showed a potential of full-waveform ALS data to classify trees, grass and ground points in orange orchard. They used backscattering coefficient with pulse width and obtained 91% of classification efficiency.

DISCUSSION

The paper presents an overview of methods for estimating tree geometric parameters from ALS data. A variety of methods for treetop identification, crown delineation in 2D and 3D approach, estimation of tree geometric parameters, namely: tree height, crown base height, crown diameter and crown volume are discussed here.

Among the overviewed and cited papers, most of the studies concerned coniferous forests (74%) or mixed forest (21%), while only few studies investigated deciduous trees (5%). Figure 2 presents the frequency of investigated tree species in study area by researchers after year 2000. One can see that coniferous trees (mainly spruce and pine) were present in almost half of the studies, while deciduous trees (mainly birch, oak and beech) were present in less than one third of overviewed papers. It is important to note, that deciduous trees were present mainly in studies that concern mixed forest in which coniferous trees were still dominant species. This is because area of studies were usually located in Scandinavian countries (Finland, Sweden, Norway) and Alpine countries (south Germany, Switzerland, Austria and Italy). Although the forest type frequency and tree species composition presented here were made based on limited number of papers, that may be considered as representative ones, showing that the methods are mainly developed for coniferous forest areas. The dominance of coniferous in forestry studies is a potential threat in applying forestry methods for agricultural trees, which are deciduous trees. It should be expected, that the methods will not be optimum in the sense of the quality of the results and complexity of the processing strategy.

If available, information about the ALS data density and efficiency of single tree detection was extracted from the research cited in this paper (only the papers published after year 2000 were analysed). The objective of Figure 3 was to analyse if there is a significant improvement in tree detection methods over last years. Figure 4 was prepared to study if high density ALS data improves the results. Results are presented separately for coniferous and deciduous trees. It was found that the success rate of detected trees over last decade varies between 44 to 89% for coniferous trees and between 40 to 64% for deciduous trees. This is a serious drawback of the existing methods, especially in the context of agricultural studies, in which deciduous trees are of interest. No significant improvement was observed over the last decade (see Fig. 3). Moreover, as shown in Figure 4, processing of ALS data of higher density does not improve the tree identification process and even with low density data it is possible to obtain very good results. This is a very promising result in the context of agricultural studies, because low density data can be acquired fast, in regular basis and with reasonable cost. Moreover, for many regions and countries low density ALS data are available free of charge, however their topicality may be poor, because the update frequency is usually low.

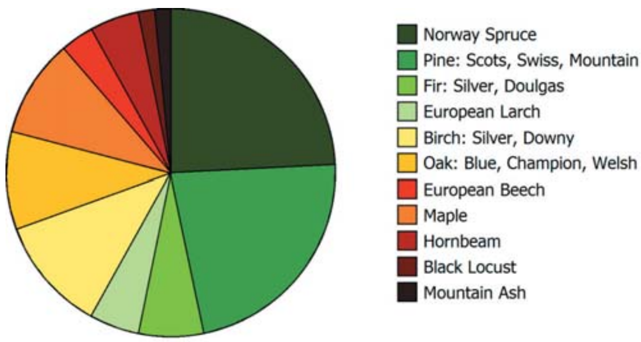

Fig. 2. The incidence of tree species among overviewed papers published after year 2000

In Table 1 it was shown, that the general approach of identifying treetops from ALS data, that are further used as a seed points for crown delineation, was based on the local maxima detection at CHM. It should be noticed that CHM is a raster created from ALS data and it’s resolution should be adjusted to ALS density. The quality of CHM depends directly on the quality and spatial resolution of both DTM and DSM. Usually a low-pass Gaussian filter is performed on the CHM raster to remove the noise. Therefore, it is required to define several processing parameters for this filter: window size, window shape and pixel weights. The disadvantage of this approach is that optimal parameters do not exist. Many researchers performed trial and error approach to visually assess the quality of the results or used the parameters proposed by other researchers for different study areas, which may result in poor performance. It should be also noted, that low-pass Gaussian filter may remove the information about truly existing trees e.g. in case treetops are very close to each other, leading to omission errors (large filtering window or too many iterations). On the other hand, unfiltered noise (small window, single iteration) may lead to commission errors. It may seem that for agricultural trees tree identification is not a problem, because trees are usually planted within a distance. However, in old orchard, tree crowns often touch neighbouring crowns, and they are not subject of further pruning to ensure maximum yields. In this case, tree top identification becomes problematic, because crowns of agricultural trees have no conical shape like coniferous trees, but the top surface of crown is rather flat, spherical or irregular. Especially in the latter case, is may be difficult to distinguish trees and detect only one treetop for a single tree.

Taking into consideration the above two paragraphs it can be concluded that the successful tree identification is highly conditioned by forest stand characteristics (tree species, forest age and density), while data density and processing strategy is of secondary importance. It is important to note that the success rates presented in Figures 3 and 4 refer to different study areas, so they cannot be compared directly.

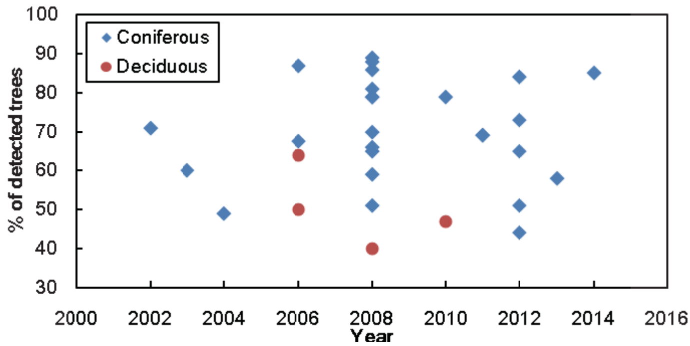

Fig. 3. The efficiency of tree detection methods reported by researchers after year 2000

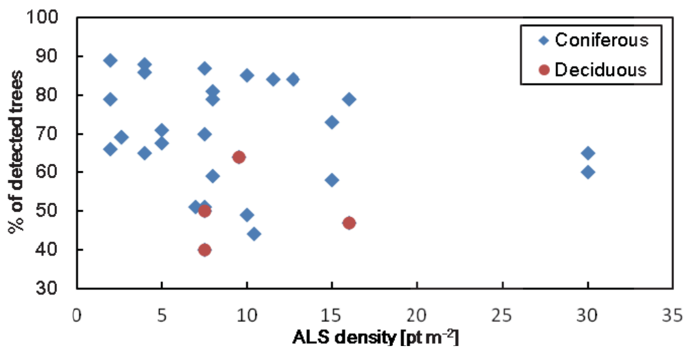

Fig. 4. The dependence between ALS data density and efficiency of tree detection methods, as reported by researchers (research after year 2000 are considered)

Among the methods for crown delineation, 2D approaches are dominant. These methods are based on CHM analysis, therefore they efficiency directly depend on CHM quality. The methods are sensitive to treetop identification. Only the classical watershed transformation can perform without initial definition of seed point, but the results are not as good as in marker-controlled watershed approach, that requires object marker definition. Moreover, in region growing approach some constraints are imposed on the tree crown outline. In particular, only "star shape" type objects (that represents well only regular shapes) are allowed. Therefore it may lead to incorrect delineation of tree crowns of irregular shapes e.g. broad crowns, vase crowns and layered crowns as well as crowns being subject of pruning. Watershed transformation and pouring methods were originally developed for relief analysis and were adopted for forestry studies, so the results obtained with these methods usually requires further processing e.g. iterative segmentation and merging of defined outlines. It seems there are no contradictions to adopt forestry methods of tree crown delineation for agricultural trees. It should be investigated how to set parameters of methods and which method performs the best.

It is still a challenging task to separate crown of overlaying trees, especially for deciduous trees. The efficiency of methods decreases for small trees and with increasing forest density. For this reason several researchers suggested to move towards 3D analysis. These methods, however, require high density ALS data. A drawback of voxel space approach is that trees, that were not identified in the top layer, will not be identified at all or merged to other trees. Therefore, this method is not suitable for areas covered by trees of significantly varying heights. It is also sensitive to voxel dimensions. It is desired to define not uniform voxel space, but none of the research indicates the method of voxel space dimensions other than by trial and error approach. An alternative method for 3D crown delineation is k-means approach that is also not free of drawbacks. It tends to create ball shaped segments, so researchers apply downscaling factor for CHM heights to overcome this problem. However, the value of this factor is again tuned by trial and error approach. In agricultural studies only limited cases of overlaying trees are expected, so 3D approach is probably too complex for agricultural trees.

The strategies of tree geometric parameter estimation can be divided into two approaches: without and with reference data. In case no reference data is available, only straightforward measurements on ALS data classified for individual tree can be performed. This may lead to the occurrence of systematic errors. Tree heights are usually be underestimated because of limited probability that the laser beam hits the treetop. For similar reasons crown base height will usually be overestimated or they can be mixed among overlaying trees. Finally, crown diameter and crown volumes will directly depend on the quality of delineation process in 2D and 3D respectively. If a reference data are available it is recommended to use linear regression model that transform explanatory variables (e.g. plot characteristics) to final estimates of tree geometric parameters. With number of field measurements and great number of features it is possible to apply random forest method, that runs efficiently even on large data sets. The main disadvantage of both regression model approach and random forest approach is that field measurements are required, that were performed at this particular study area. Created models cannot be considered as versatile, because each tree species and study area varies significantly. In general, the methodology for tree geometric parameters estimation is very straightforward, so it should be easy to adopt this strategy for agricultural studies. It should be investigated if the quality of the results is sufficient for agricultural management and planning. In case of the approach with reference data, it should be investigated which and how many parameters should be measured in the field to build a reliable regression model.

The presented methods for tree identification, crown delineation and geometric parameter estimation were originally developed for forest areas and usually better results are obtained for coniferous trees than deciduous trees. So far, only limited studies were performed for agricultural trees, which have, after all, different structure than forest trees – they have short stem with a biomass located mainly in the crown. Moreover, forest trees are usually close to each other, supressed, with overlapping crowns, while the agricultural trees are kept at a distance, due to artificial planting and regular pruning. Still, there is very few research related with the use of ALS data for agricultural areas. It seems that for agricultural trees the potential of ALS data is still unexplored and undervalued.

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PRZEGLĄD METOD ESTYMACJI PARAMETRÓW GEOMETRYCZNYCH DRZEW Z DANYCH ALS W KONTEKŚCIE ICH APLIKACJI DLA DRZEW UPRAWNYCH

Streszczenie. Celami pracy są przegląd oraz analiza istniejących metod estymacji parametrów geometrycznych drzew na podstawie danych lotniczego skaningu laserowego w kontekście ich aplikacji dla drzew uprawnych. W artykule przedstawiono szczegółowy opis metod estymacji tych parametrów stosowanych przez różne grupy badawcze. Opis uwzględnia budowę wysokościowego modelu koron, identyfikację drzew, identyfikację kształtu koron w 2D i 3D, estymację wysokości drzew, wysokości podstawy koron, średnic oraz objętości koron. Wskazano zalety i wady zaprezentowanych metod. Przeanalizowano także, czy opisane metody rozwinięte na obszarach leśnych mogą być wykorzystywane w przypadku drzew uprawnych.

Słowa kluczowe: ALS, drzewa, rolnictwo, teledetekcja

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