INDIVIDUAL TREE IDENTIFICATION USING COMBINED LIDAR DATA AND OPTICAL IMAGERY

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Abstract
The most important part in forest inventory based on remote sensing data is individual tree identification, because only when the tree is identified, we can try to determine its characteristic features. The objective of research was to explore remote sensing methods to determine individual tree position using LiDAR and digital aerial photography in Latvian forest conditions. The study site was a forest in the middle of Latvia – in Jelgava district (56º39' N, 23º47' E). Aerial photography camera (ADS 40) and laser scanner (ALS 50 II) were used to capture the data. LiDAR resolution was 9p m^2 (500 m altitude). The image data is RGB, NIR and PAN spectrum with 20 cm pixel resolution. Image processing was made using Fourier transform, frequency filtering, and reverse Fourier transform. LiDAR data processing methods was based on canopy height model, Gaussian mask, and local maxima. Field measurements were tree coordinates, species, height, diameter at breast height, crown width and length. Using combined LiDAR and optical imagery data allows detecting at least 63% of all trees and about 85% of the dominant trees.
Key words: Forest inventory, tree identification, laser scanning, aerial photography, data fusion.

Introduction

Various studies concentrate on individual tree detection from different remote sensing data. An optimal tree identification method often consists of a variety of data sources that are combined with various methods (Hyyppä et al., 2008). Most common sensors for forestry measurement applications are Airborne LiDAR (Light Detection and Ranging) and digital aerial cameras. LiDAR is one of the active optical remote sensing technologies that can provide highly accurate measurements of both the forest canopy and the ground surface. It provides data that make it possible to identify and isolate individual trees. Different sensors or methods that encompass certain levels of observation should not be taken as exclusionary alternatives (Korpela et al., 2004).

The most responsible and important part in forest inventory based on remote sensing data, is individual tree identification, because only when the tree is identified, we can try to determine its characteristic features like tree species, tree height, diameter at breast height, volume, and biomass (Secord and Zakhor, 2006; Edson and Wing, 2011).

In studies of forest inventory using remote sensing sensors, one of the main problems the authors mention is tree identification and accurate determination of the tree location (Hyyppä et al., 2008; Kane et al., 2010), especially in Middle Europe (Diedershagen et al., 2006), since there is a mixture of different deciduous and coniferous trees. As a result, the indication is much harder. Many authors in their conclusions highlight that the usage of LiDAR and airphoto methods to determine forest inventory parameters will never be one hundred per cent correct (Onge et al., 2004; Rombouts, 2006), especially applying automated tracking methods (Hyyppä et al., 2004; Junttila et al., 2010). Practically for all researchers so far it has been difficult to identify small trees (Pitkänen, 2001; Pouliot and King, 2005) and close existing trees (Pouliot and King, 2005; Koch et al., 2006), as well as high density hardwood stands with homogeneous crown (Kocha et al., 2006; Rahman and Gorte, 2008). Automated tree identification and accurate determination of the tree location is still problematic (Popescu et al., 2002; Junttila et al., 2010), even in cases where access to different types of data (Vauhkonen et al., 2008) is available. This is mainly explained by the fact thattrees vary in crown size (Tokola et al., 2008), shape and optical properties (Tokola et al., 2008; Vauhkonen et al., 2008), for example, some species have rounded crowns, some have cone-shaped crowns, and some have star-shaped crowns. Tone in aerial photographs depends on many factors, and relative tones on a single photograph, or a strip of photographs may be of great value in delineating adjacent trees of different species (Kocha et al., 2006). Crowns are often interlaced. Occlusion and shading are present, and result in omission errors. These factors affect the treetop positioning and make the identification of trees difficult.

Pitkänen developed several methods for individual tree detection based on canopy height model of Airborne LiDAR. One of them he used a Gaussian filter to determine equalized height of pixel. Local maxima and smoothed Canopy Height Model were considered as tree locations. In the other method, large numbers of possible tree locations were selected based on local maxima. The pixels were reduced based on slope within the assumed crown center area and based on the distance and valley depth between a location and its neighboring locations. The second method used crown width and tree height model as a parameter to adapt with tree size. Both methods showed that about 60-70% of the dominant trees were found (Pitkänen et al., 2004). Weinacker used local maximum of smoothed canopy height model and delineation of single tree is done using pouring algorithm. It was observed that the segmented trees still contained a lot of wrong segments, in which the regions are too small to be a tree, inappropriate crown shape, and crown regions that cover another trees and canopy gaps. The segments were refined based on their shapes and distance between tree tops (Weinacker et al., 2004). In another study, Kim used variable size of local maxima filtering window with the assumption that there is a relationship between crown size and tree height. It was shown that the regression coefficients are less than 0.6 (Kim et al., 2008). In Scandinavian countries, studies of tree location determination using LiDAR and digital aerial camera show good results. For example, Korpelas research shows that location of 2% of conifers and 10% of deciduous trees were determined inaccurately, 10% of all trees were not identified, and 12% of the total stock of wood was inaccurate (Korpela, 2006). Falkowski introduces technique based on spatial wavelet analysis to automatically estimate location, height and crown diameter of individual trees using Airborne LiDAR. The advantage of this method is that no knowledge on tree height and crown diameter relationship is required (Falkowski et al., 2006).

Numbers of different methods are used to identify a single tree using Airborne LiDAR and digital aerial cameras. Above it is clearly shown that most of the tree detection studies were based on the height of the canopy. For some approaches the relationship between crown size and tree height is needed beforehand. Single-scale template matching has been successfully applied in 2D and 3D treetop estimation of regular stands, where crowns show only moderate variation (Korpela and Tokola, 2006). In contrast, to determine all the treetops where forest foliage is complex in structure and with a large variation, the most appropriate are the automatic and semi-automatic methods (Korpela et al., 2007).

Data collection and processing methods in different conditions work variously, mainly due to forest density, represented tree species and forest diversity in growing conditions, as well as LiDAR and optical imagery. The objective of research is to explore methods to determine single tree position using LiDAR and digital aerial photography in Latvian forest conditions.

Materials and Methods

The study site was a forest (12 700 ha) in the middle of Latvia - in Jelgava district (56º39’ N, 23º47’ E). Totally 350 sample plots (0.045 ha) were established during the summer of 2011.

The area consists of a mixed coniferous and deciduous forest with different age, high density, complex structure, various components, composition and soil conditions.

Represented species were Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* (L.) H.Karst), silver birch (*Betula péndula* Roth), black alder (*Alnus glutinos* L.), and European aspen (*Populu strémula* L.).

All trees with a diameter at breast height (DBH) of more than 5 cm were measured, and for each tree coordinates, its species, height, DBH, crown width and length were recorded. Altogether there were 6155 trees in the data. The mean characteristics of all trees are presented in Table 1.

Differentially corrected Global Positioning System measurements were used to determine the position of each plot center. The accuracy of the positioning was approximately 1 meter.

The tree crown width was measured by projecting the edges of the crown to the ground and measuring the length along one axis from edge to edge through the crown center. The diameters of any two axes at 90 degrees to each other were selected and averaged using an arithmetic mean. Tree locations within a plot were measured using center as the origin and then determining tree azimuth and distance to the center.

In data processing, effective crown area (area that does not overlap with another tree crown) for each tree (first and second storey trees equally) was calculated using information about its locations within a plot and crown width. The foliage was projected on the ground, and using the generally known area calculation formulas the effective crown area was calculated.

Data were obtained using a specialized aircraft Pilatus PC-6, which is equipped with a positioning and Geomatics technology company Leica Geosystems equipment a large format digital aerial photography camera (ADS 40) and laser scanner (ALS 50 II). The study area was flown over by plane and scanned at three different altitudes. The LiDAR digital terrain models (DTM) were estimated from leaf-on data from May, 2010, having 9 p m^{-2} at 500 m altitude. The image data are RGB (Red, Green, and Blue*)*, NIR (Near Infrared*)* and PAN (Panchromatic) spectrum with 20 cm pixel resolution.

Fourier transform, frequency filtering and reverse Fourier transform were performed to each image from the previously prepared data sets. After this process, texture of image was obtained. Fourier transform function:

$$F\,(k,l) = \sum_{j=0}^{N-1} \sum_{j=0}^{N-1} f(i,j)\, e^{-t2\pi(\frac{ki}{N}+\frac{lj}{N})}, \quad (1)$$

Fourier frequency filtering function:

$$G(k,l) = F(k,l)\,H(k,l)\,, \tag{2}$$

Reverse Fourier transform function:

$$f\,(i,j) = \frac{1}{N^2}\sum_{k=0}^{N-1}\sum_{i=0}^{N-1} F(k,l)e^{\,t2\pi(\frac{ki}{N}+\frac{lj}{N})}\,, \tag{3}$$

where f (i,j) is the image in the spatial domain, and the exponential term is the basis function corresponding to each point F (k,l) in the Fourier space. H (k, l) is the simplest case, the threshold function that determines which frequencies to keep and which not. N is used for normalization.

Eight different convolutions where made with 15×15 matrix after applying a Fourier filter (matrix size is related to the projection image pixel size), in resulting image pixels where highlighted that match at specified filter. Discrete filter convolution mathematical definition is as follows:

$$F\,(i,j) = \sum_{x=0}^{m}\sum_{y=0}^{n} F'\left(i+\left(x-\frac{m}{2}\right),\; j+\left(y-\frac{n}{2}\right)\right)K(x,y) \tag{4}$$

where F (i, j) result of image pixel; F ‘(i, j) the original image pixel; C (x, y) convolution filter matrix value; m, n convolution filter matrix dimensions.

Information about filter configuration was highlighted after image processing with convolution matrices. To find the peak that matches the tree center, all eight files were calculated and a single image, which retains only the pixels in the convolution execution of all eight images with the same intensity, was created. Image overlay was used to find this function:

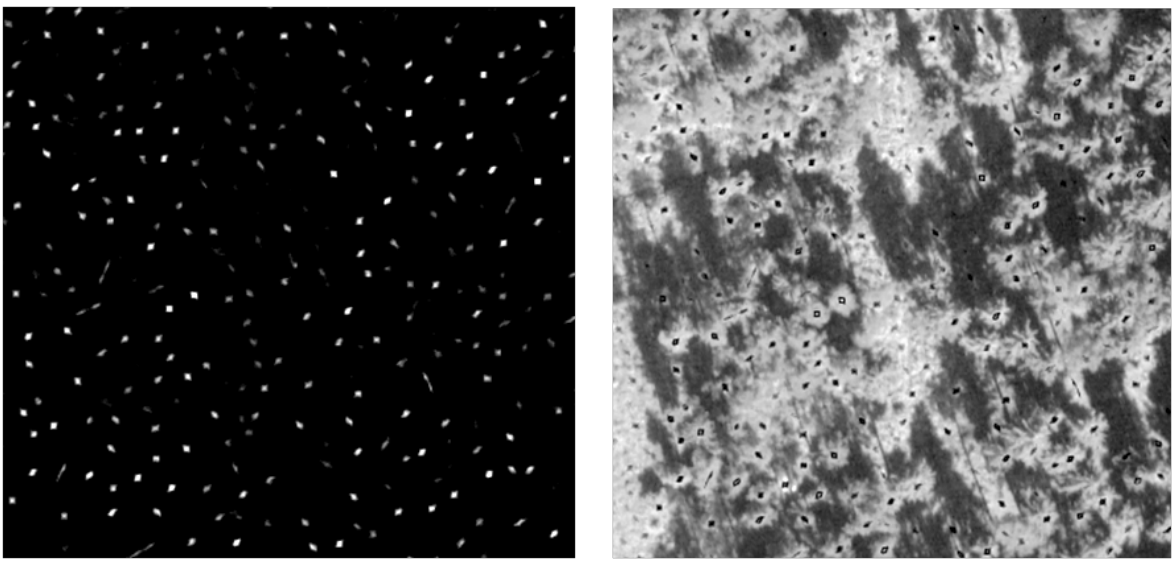
$$F(i,j) = \min\,\left(I(i,j), L(i,j)\right) \tag{5}$$

where I (i, j) and L (i, j) coated image pixel values. The result is a picture where the intensity of pixels corresponds to the largest tree in the center (Figure 1. (a)).

There are many additional points that are not only on trees, but also on other objects, therefore, it is necessary to perform data filtering. Once the information need is imported in database, it is possible to make the necessary filtering and combining operations with LiDAR tree centers. Before importing each pixel high-intensity group (which serves local maxima) are defined. Center and its geographical coordinates are calculated using the image geo-referenced data.

The individual tree detection and identification method is based on canopy height model. The model was smoothed using a Gaussian mask, and the degree of smoothing is defined by the height of pixel. Subsequently, local maxima on the smoothed canopy height model were considered as tree locations. Noisy data was masked (suppressed) using 5×5 Gaussian mask size (Figure 2. (c)).

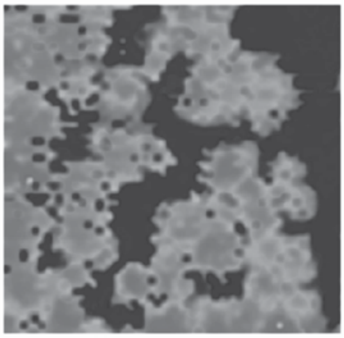
With Gaussian mask each point value was calculated taking into account the impact of the points placed beside. The closest points have a greater impact, but the further - a smaller impact. In the middle of the Gaussian matrix the highest value indicating the significance is located, and this value is multiplied by the point value. After calculating the



a) Local Maxima.

b) Local Maxima combined with the original image.

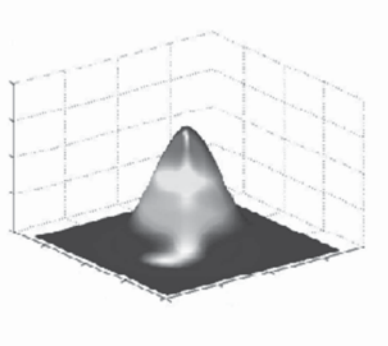
Figure 1. Result of convolution process.



a) Raw LiDAR data.

2	4	5	4	2
4	9	12	9	4
5	12	**15**	12	5
4	9	12	9	4
2	4	5	4	2

b) Gaussian mask matrix for a single tree.



c) Gaussian masks result for a single tree.

Figure 2. LiDAR data processing.

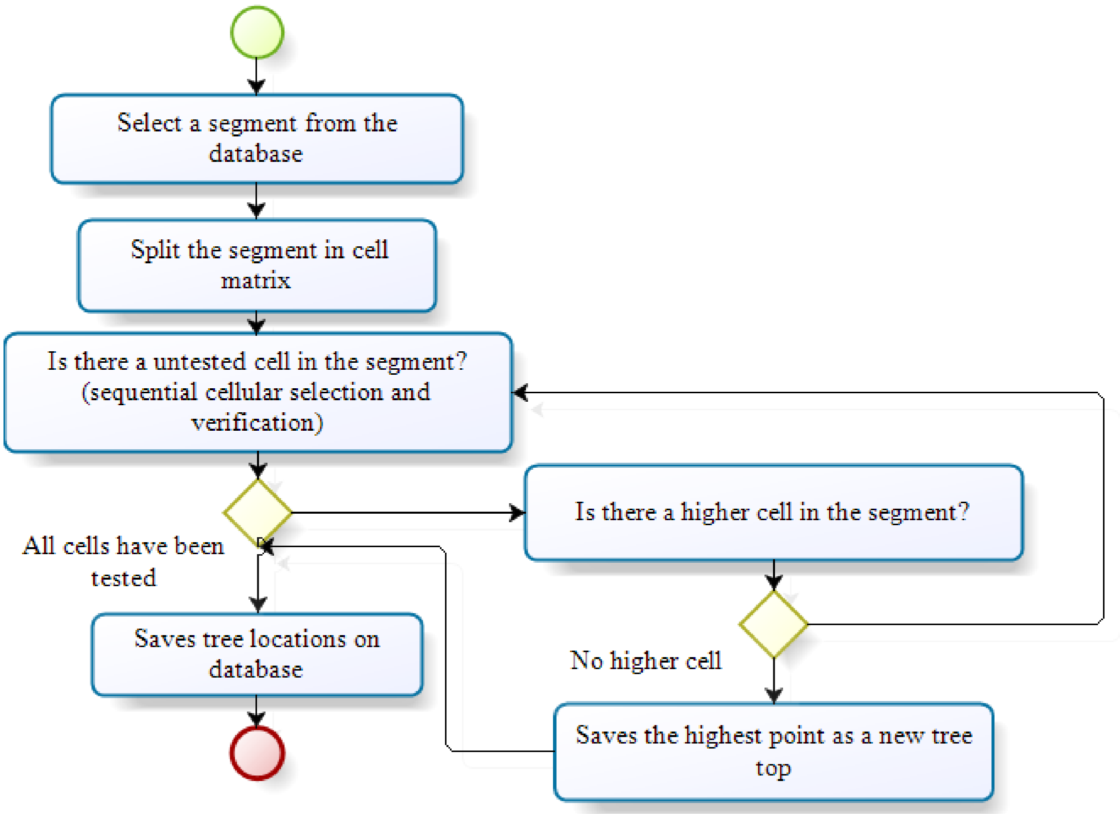


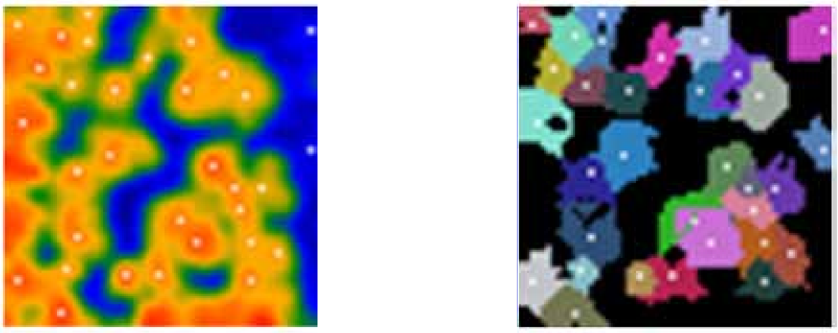
Figure 3. Tree recognition algorithm.

Gaussian mask, the highest segment points above the surface were searched and compared with adjacent cells independently of each segment. If the selected cell was higher than the adjacent, then there was the tree top. Tree top not always is the center of the cell, so the tree is found in the center of determining the highest cell. Tree recognition algorithm is shown in Figure 3.

Results and Discussion

The accuracy of tree detection was satisfactorily when we used combined LiDAR and optical imagery data. Figure 4 shows the identified tree centers detected in the canopy height model using a Gaussian mask and local maxima.

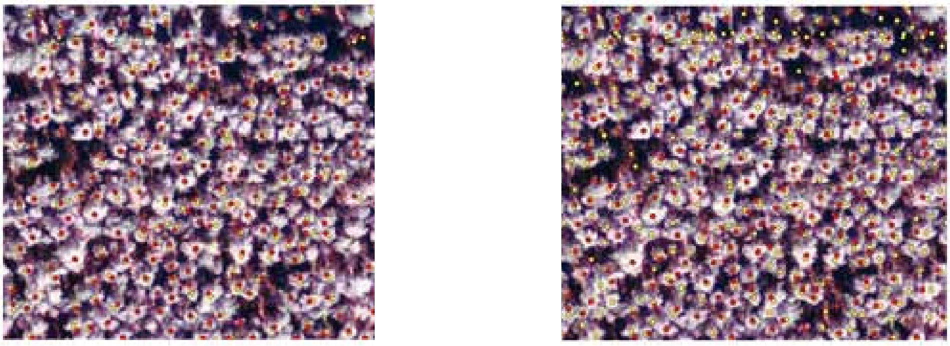
The results of identified trees using LiDAR and image data processing methods combined and separately, are showed in Figure 5. The red point shows the identified trees from an aerial photography, but the yellow one - from LiDAR. Initially, looking at these pictures it seemed that most of the trees are recognized, especially looking at the picture b), but comparing the data to field plots, omission errors were found. This was mainly caused by the large number of suppressed, small trees that were not detected from the canopy height model. The local maximum method



a) Tree top recognition result of Gaussian mask.

b) Tree locations produced by the local maximum and foliage segmentation methods.

Figure 4. Tree identification results using LiDAR and image processing methods separately.



a) Tree centers are determined by the LiDAR processing and image processing techniques separately.

b) Tree centers are determined combining both processing methods.

Figure 5. The results of identified trees using LiDAR and image data processing methods combined and separately.

partially recognized the second storey trees, which cannot be seen in the aerial photo, because they are obscured by trees on the first storey, but in aerial photo sometimes it is possible to see trees that are not visible in the LiDAR data, because when trees are close together LiDAR combines them.

The results of tree detection using combined LiDAR and aerial photographic method show that 63% of all trees were unambiguously found, but 37% of trees were not identified (Table 1). If we look at not identified trees, then 82% of cases were trees with diameter at breast height (DBH) less than 20 cm, and 88% of cases were trees with height less than 20 m. This means that only about 15% of first storey trees were not identified correctly.

The calculated tree centers only in 86% of cases are located in 3 m limit. This is explained by the fact that trees vary in crown size, shape and optical properties, and crowns are often interlaced. These factors affect the treetop positioning and make the identification difficult.

Descriptive statistics of tree detection result and tree characterizing parameters (combined LiDAR and optical imagery data) is shown in Table 1, and analysis of variance between tree detection result and tree characterizing parameters is shown in Table 2.

Analysis of variance between tree detection result and tree characterizing parameters shows that only tree age is not statistically significant at a different level of significance. This means that the tree height, diameter at breast height and tree crown width affect the possibilities of identifying trees from remote sensing data.

In literature, using a similar approach, the tree identification results show variable results. I. Korpelas study reveals that 91% of conifers and 86% of the deciduous trees were identified using the local maximum filtering method (Korpela, 2006), but H. Weinacker in his study found that only 54% of trees were identified correctly (Weinacker et al., 2004). At the same time, S. Kim suggests that 64% of all the trees can possibly be identified (Kim et al., 2008). In many works, the authors mention that the forest type and the dominant species are the main factors that affect tree identification possibilities (Pitkänen et al., 2004; Kocha et al., 2006; Korpela, 2006; Tokola et al., 2008).

Table 1

Descriptive statistics of tree detection result and tree characterizing parameters (combined LiDAR and optical imagery data)

Result of tree detection		Age	DBH	Tree Height	Crown Width
Trees identified	Mean	68.73	25.857	23.655	5.8929
	N	3857	3857	3857	3857
	Std. Deviation	34.308	10.1293	6.3165	2.02080
	Minimum	4	5	3.5	1.13
	Maximum	164	83.8	39.9	18.93
	% of Total N	62.7%	62.7%	62.7%	62.7%
Trees not identified	Mean	68.74	14.262	13.612	4.3950
	N	2297	2297	2297	2297
	Std. Deviation	35.099	7.2307	5.6882	1.58273
	Minimum	4	5	1.9	0.50
	Maximum	164	54.6	37.3	13.31
	% of Total N	37.3%	37.3%	37.3%	37.3%

Table 2

Analysis of variance between tree detection result and tree characterizing parameters

	Sum of Squares	Mean Square	F	Sig.
Age * Tree Detection Result	0.041	0.041	0.000	0.995
DBH * Tree Detection Result	193552.115	193552.115	2309.059	0.000
Tree Height * Tree Detection Result	145217.109	145217.109	3916.008	0.000
Crown Width * Tree Detection Result	3230.005	3230.005	924.320	0.000

Conclusions

1. Using combined LiDAR and optical imagery data it is possible to detect at least 63% of all trees and about 85% of the dominant trees. This is explained by the fact that trees vary in crown size, shape and optical properties, and crowns are often interlaced. These factors affect the treetop positioning and make the identification difficult. The problem is with the identification of the small trees and close existing trees, as well as with high - density hardwood stands with a homogeneous crown.
2. Analysis of identified trees shows that Norway spruce was not identified in 20% of cases and 55% at the species level trees were not identified. This is explained by the fact that the spruce crown geometry is triangular, and, consequently, the LiDAR - transmitted pulses often miss the highest tree point. Pine and birch crown geometry is slightly flatter, and the measurements are more accurate.
3. Latvian forest conditions are difficult for single tree remote sensing methods mainly of mixed deciduous and coniferous species with a high level of the second storey trees in one stand. Mostly trees are close together at high density and with a homogeneous crown. It is one of the main reasons for a large number of trees that are omitted.
4. To improve the recognized number of trees, one way is to perform laser scanning in spring when the forest is less dense, the first storey trees are more transparent, and the smaller dimension trees can be recognized. A second way is to use tree crown shape analyze from LiDAR data, and it means that there is a need for LiDAR data with a higher level of point density per square meter.

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