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original scientific article

Individual tree identification using different LIDAR and optical imagery data processing methods

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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 is to explore remote sensing methods to determine individual tree position using LIDAR and digital aerial photography in Latvian forest conditions. The study site is a forest in the middle of Latvia at Jelgava district (56º39' N, 23º47' E). Aerial photography camera (ADS 40) and laser scanner (ALS 50 II) were used to capture the data. A LIDAR data is 1.4 to 9 p/m2 depending on the altitude. Image data is RGB (Red, Green, and Blue), NIR (Near Infrared) and PAN (Panchromatic) spectrum with 20 to 50 cm pixel resolution depending on the altitude. Image processing was made using Fourier transform and RGB colour segmentation. LIDAR data are processed with DBSCAN algorithm, global maximum algorithm, and local maximum algorithm. Field measurement's parameters were tree coordinates, species, height, diameter at breast height, crown width, and length.*
Best results on both ALS and ADS data were achieved using local maximum methods.

Keywords: Forest inventory, tree identification, laser scanning, aerial photography, data fusion.

1. Introduction

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 et al., 2006; Edson and Wing, 2011).

In the studies of forest inventory using remote sensing sensors, one of the main problems that the authors mentioned is tree identification and tree location accurate determination (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 identification is more difficult. 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 closely growing trees (Pouliot and King, 2005; Koch et al., 2006), as well as high density hardwood stands with homogeneous crown (Koch et al., 2006; Rahman and Gorte, 2008). Automated tree identification and tree location accurate determination are still problematic (Popescu et al., 2002; Junttila et al., 2010), even in cases where different types of data (Vauhkonen et al., 2008) are available. This is mainly by the fact that trees 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 a great value in delineating adjacent trees of different species (Koch 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.

Several methods are used to identify a single tree. The main criterion for choice of identification method is the specific structure of forest canopy and species diversity. If the area of construction is more complicated, tree locations and their exact coordinates are difficult to determine. Single-scale template matching has been successfully applied in 2D and 3D treetop estimation of regular stands, where crowns show only moderate variation (Korpela, 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).

Pitkanen developed several methods for individual tree detection based on canopy height model of Airborne LIDAR. In one of them, he used a Gaussian filter to determine equalized height of pixel and local maxima on the 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 the slope within the assumed crown centre area and based on the distance and valley depth between a location and its neighbouring 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 (Pitkanen et al., 2004).

Heinzel 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 (Heinzel et al., 2008).

Data collection and processing methods at different conditions work differently, mainly due to forest density, represented tree species and forest diversity in growing conditions, as well as LIDAR and digital aerial cameras technology specifics.

The objective of research is to explore methods to determine single tree position using LIDAR and digital aerial photography in Latvian forest conditions.

2. Materials and methods

The study site is a forest in the middle of Latvia in Jelgava district (56º39' N, 23º47' E). The area consists of mixed coniferous and deciduous forest with different age, high density, complex structure, various components, and composition. Represented species are pine (*Pinus sylvestris L.*), spruce (*Picea abies (L.) H.Karst*), birch (*Betula pendula Roth*), and aspen (*Populus tremula L.*).

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. A LIDAR digital terrain models (DTM) were estimated from leaf-on data from May, 2010 having 9 p/m2 at 500 m altitude; 3.7 p/m2 at 1000 m altitude; 1.4 p/m2 at 1500 m altitude.

The image data is RGB (Red, Green, and Blue), NIR (Near Infrared) and PAN (Panchromatic) spectrum with 20 cm pixel resolution at 500 m altitude; 30 cm pixel resolution at 1000 m altitude; 50 cm pixel resolution at 1500 m altitude.

In the study area, 10 sample plots were selected to analyze accuracy of different tree identification methods and to determine impact of the resulting ALS and ADS data structures on the number of trees identified. Plots were chosen to be simple by the structure with small proportion of the tree on the second floor.

In order to determine the best method ALS data with 9 p/m2 and ADS data with a pixel size of 20 cm in the field were used.

It should be noted that the choice of methods was based only on the number of trees identified in all the plots together, without analyzing them over the tree species or forest floors or other woodwork characterizing parameters.

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 252 trees in the data. Circular sample plots were established with dimensions of 0.045 ha.

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

2.1. LIDAR data processing methods

Three different methods for tree identification were evaluated. The first method is based on reflection point count in a certain height range. It was made by adopting density based clustering algorithm (DBSCAN) (Sriperumbudur and Steinwart, 2012; Meng, 2010), which was accompanied by restrictions on the radius determination. Realization of the method is based on the number of points above a certain height level (Fig. 1).

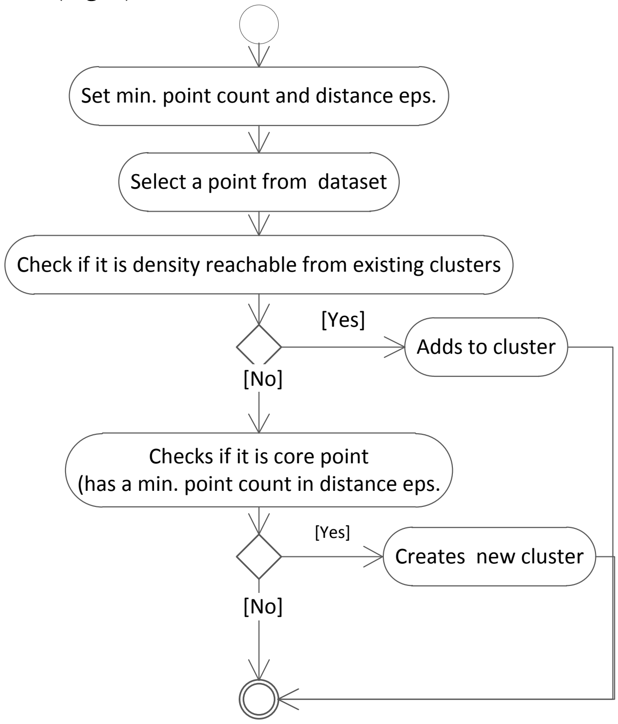

Fig. 1. **DBSCAN algorithm** (Sriperumbudur and Steinwart, 2012; Meng, 2010).

In the literature, several researchers state that this method gives good results (Meng, 2010; Sriperumbudur and Steinwart, 2012).

The second method used for processing of LIDAR data set is global maximum method (Fig. 2) that uses height data and range limitations. This method worked poorly. First, the LIDAR data set points were read, and then divided into quadrants. Afterwards cluster formed by the maximum points in the upper layer was found, and deleted from the cube. In this way, part of points belonging to other trees was lost, and trees were omitted.

The third method used was searching for local maximums on height axis of LIDAR data collection. Use of this method is based on the assumption that tree top centre is the highest point in data set which is not always the case. This method is used on LIDAR data that are smoothed by using Gaussian mask. As closest point of such mask has bigger affect than the ones on the border. It can be stated that this filter evaluates between point interactions. After calculating the Gaussian mask the highest segment points above the surface were searched and compared with adjacent cells independently each segment. If the selected cell is higher than the adjacent - then there is the tree top. Tree top is not always the centre of the cell, so the tree is found in the centre of determining the highest cell. Tree recognition algorithm is shown in (Fig. 3).

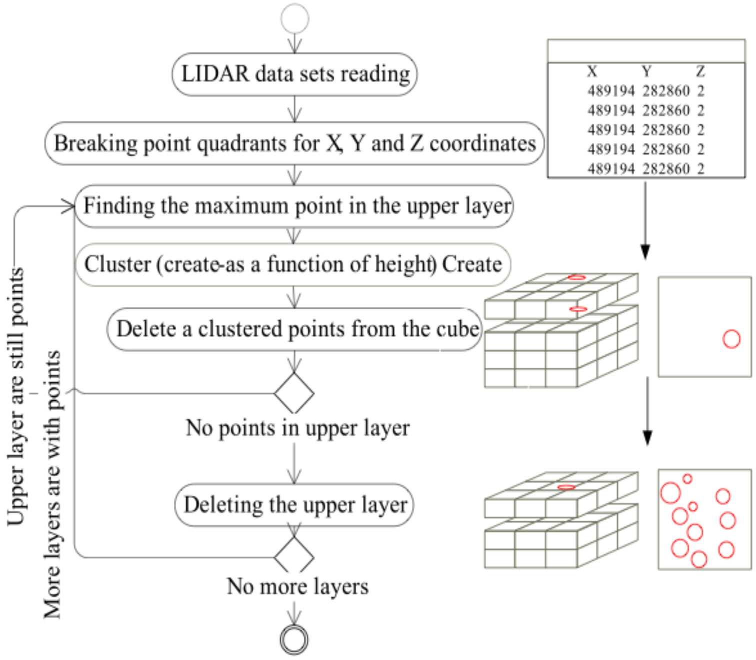

Fig. 2. **Global maximum algorithm.**

The described local maximum approach is one of the most widely used methods of tree identification, and determination of the crown canopy tree height determination (Pikanen et al., 2004; Popescu, 2003; Korpela, 2006; Korpela, 2007).

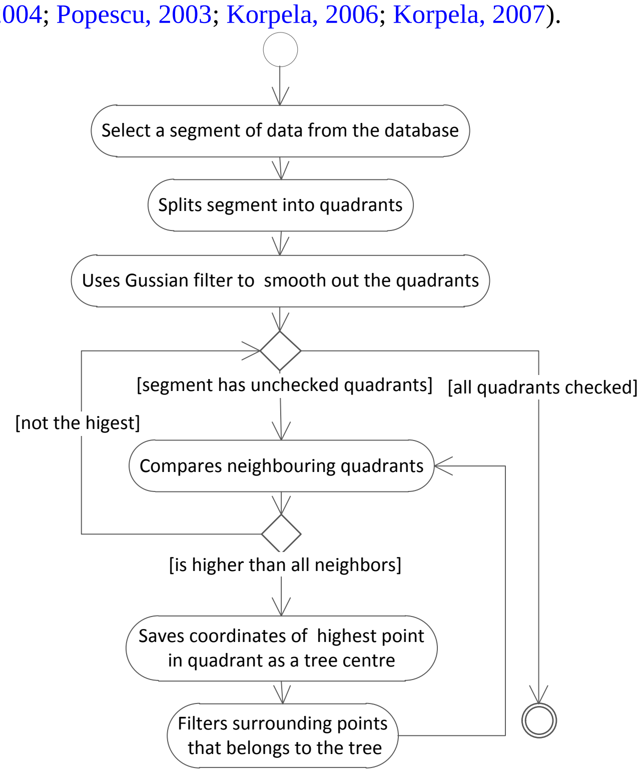

Fig. 3. **Local maximum algorithm.**

In the course of evaluating the capability of identifying trees using ALS data, all three methods were examined, and for future use on the local maximum approach and the Gaussian filter were chosen as these approaches showed the best result in practical sample plot tests.

2.2. Image processing methods

RGB colour segmentation is one of the most commonly used image processing methods (Crosilla, et al., 2005), and in this research it was considered as an alternative to the local maximum approach (described later). Two phase process that consists of image preparing and processing steps was realized for tree identification using a segmentation method. In the image preparatory phase, smaller images from the aerial photographs were created and geographical information for each of them was stored. In segmentation process, each image was divided into several regions. Result of this process is a set of segments, covering the entire image or individual object contours, that can be facilitated in further image analysis and processing tasks. All pixels in the segment have common colour, intensity, texture and other characteristics. For this study, colour segmentation algorithm that filters certain colour values specified by predefined masks was used on images green channels data.

For image processing, different algorithms can be used to improve or on the contrary - to lower quality in order to avoid some noise in the data. Still by using standard image processing algorithms it is impossible to do an automated identification. For tree identification from aerial images it is necessary to develop special algorithms and methods that are based or use classical ones in some detailed tasks. Such method can be seen in (Fig. 4).

In this method (Fig. 4), tree identification process begins with detection of a pixel that belongs to the tree canopy. Once one pixel is found in given direction, algorithm looks for the other side of segment (border pixels). In the next step, centre of the vector given by two points is found and used to search the other border points in different directions that help to establish a correct tree top centre position. Geographic coordinates for identified trees are calculated using image geo-referenced data and its pixels are excluded from the searched area. After determination of tree centre coordinates, they are imported into the database. In addition to the coordinate information, the image colour component values and all other available data are recorded for postprocessing tasks.

Tree identification through segmentation method is less labour intensive as compared to the local maximum method, as well as less complex from calculation point of view. But in the practical tests on selected sample plots it shows worse results than the local maximum method, and therefore it was not used for all sample plots in this study.

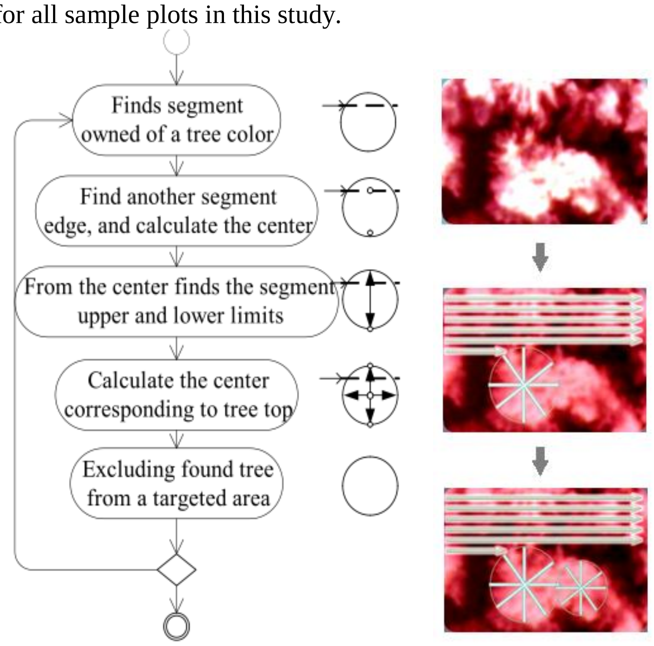

Fig. 4. **Tree colour segmentation method.**

The main method used in this study for tree identification from aerial photographs is based on the local maximum approach (Rossmann, et al., 2007; Popescu and Wynne, 2002), where using the Fourier transform process that consists of several stages- image preparation, image processing and compilation of results- is performed.

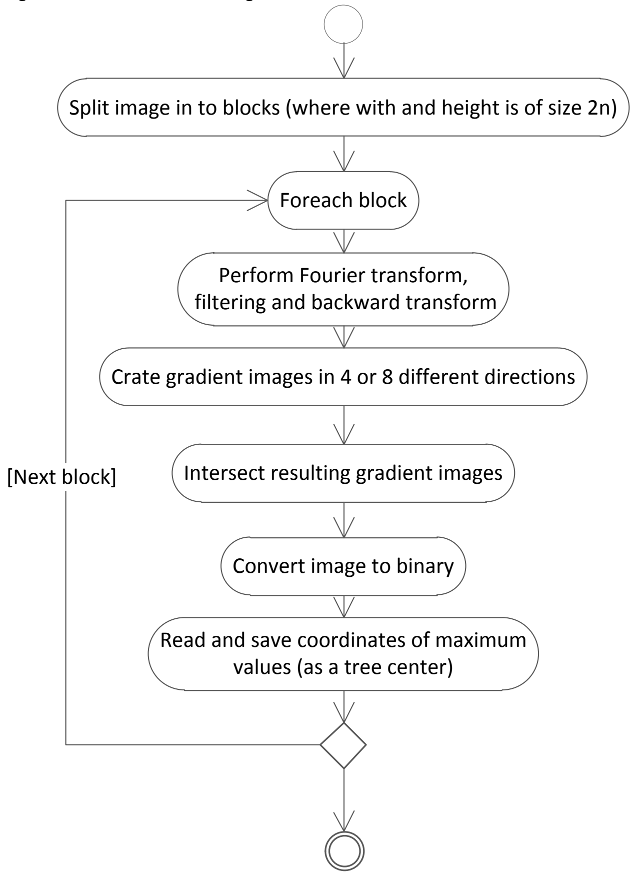

Fig. 5. **Local maximum method for ADS data.**

Fig. 5 shows main steps used in local maximum method for tree identification. It begins with image division into several sub images of size 2n. Main reason for such deviation and size restrictions is dictated by fast Fourier transformation algorithm used in next steps. After Fourier transformation each subimage is filtered and transformed back to spatial domain. In a next step gradient images in 4 or 8 different directions are calculated and intersected with each other. Then the binary image is created, by using results of previous steps such that maximal values show only local maximum points. Main reason for choosing Fourier transformation and performing filtering in frequency domain instead of simple Gaussian filtering is speed of used methods and descriptions of successful usage found in publications. Fourier transformation is described as a method of choice for tree identification (Vaughn et al., 2011; Vaughn et al., 2012; Edwards and Nesbitt, 2002), and it is also tested in tree species identification tasks (Nicholas et al., 2012).

Usage of Fourier transformation is studied both for tree position (Vaughn et al., 2011; Vaughn et al., 2012; Edwards and Nesbitt, 2002), and species identification (Nicholas et al., 2012).

3. Results and discussion

3.1. Comparison of tree identification methods used in the study

Before the remote sensing data processing 10 sample plots in the study area were selected for compliance evaluation of different tree identification methods, as well as for identification of ALS and ADS data collection altitude affects on the tree identification process. Totally 252 trees were measured in sample plots. Plots were chosen to be structurally simple, so the proportion of second floor trees is as small as possible. At first, the most accurate methods using the ALS data with 9 p/m2 and ADS image resolution with a pixel size of 20 cm in the nature were established. Results of tree identification methods employed for comparison are shown in (Fig. 6).

Then their results were evaluated on data gathered at different altitude. The results can be seen in (Fig. 7, 8) It should be noted that the comparison is based only on the number of trees identified in all sample plots together, without analyzing them over the tree species or forest floors or other woodwork characterizing parameters. Local maximum method with a Gaussian filter for ALS data and Fourier filter for ADS data were considered to be the most accurate method for identifying the trees. Consequently these methods were used for tasks of tree identification for all sample plots in the study area.

Number of researchers have successfully used DB SCAN algorithm, but in practical sample plot test the algorithm showed poor results.

Lack of precision of the global maximum method may be explained by the fact that part of the ALS data set points, after finding global maximum, is attached to a single tree and removed from future search. In this case, each wrongly deleted point can lead to some omission errors.

Weak results of tree colour segmentation algorithm of image data could be explained by the fact that several trees are considered to be as one which leads to incorrect tree count results.

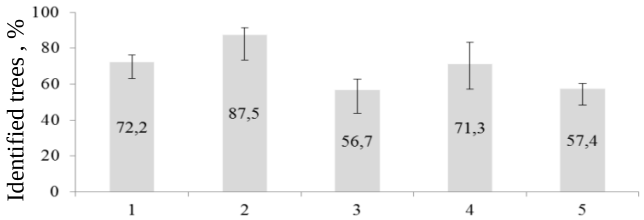

Fig. 6. **Comparison of methods for tree identification. 1- Global maximum method (ALS data used); 2 – Local maximum method with Gaussian mask (ALS data used); 3 – DB SCAN algorithm (ALS data used); 4 – Local maximum method with Fourier filtering (ADS data used); 5 – Tree colour segmentation method (ADS data). ALS data with 9 p/m2 and ADS image resolution with a pixel size of 20 cm in the nature used. Deviation intervals show the minimum and maximum values.**

Tree identification process is one of the most important stages in forest inventory, which is based on a separate survey of trees from remote sensing data, because only when a tree is identified, it is possible to perform other measurements and make predictions about forest characteristics.

3.2. Evaluation of results acquired from remote sensing data of different heights

ALS point density per square meter depends on flight altitude. So the data at different heights is processed to evaluate the effect of ALS point density change on the tree identification outcome. Fig. 7 shows percent of identified trees at different point densities.

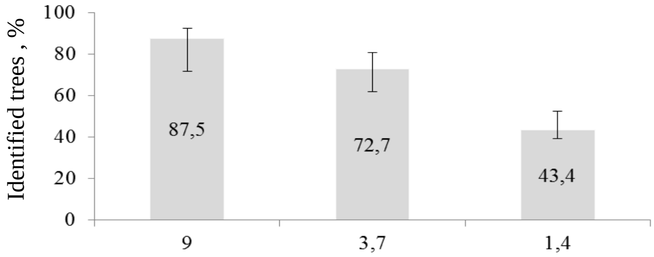

Fig. 7. **Identified trees at different point densities. The evaluation was carried out in 10 sample plots of study area (252 trees). Plots were chosen to be structurally simple, so the proportion of second floor trees is as small as possible. Deviation intervals show the minimum and maximum values.**

Best results of tree identification process are reached at the highest point density per square meter, which would be understandable, but the most interesting part is that ALS data with average point density also shows fairly good results. Although in the study for data analysis and processing mostly data with highest density were used, this evaluation shows that ALS data with average point density could be used in practice if needed.

The same as ALS data ADS image resolution depends on the flight altitude ADS. Fig. 8 shows impact of ADS resolution change (result of changing flight altitude) on results of tree identification process.

Similarly as with ALS data, the best tree identification results are achieved with higher resolution ADS images. Equivalent results show that a medium-resolution aerial photographs give fairly good results. For data analysis and processing of aerial photographs in this study, the images with 20 cm pixel size in nature were used.

In order to improve the process of tree identification, ALS and ADS data were combined. As a result, the number of identified trees in the best situation is representative of 92.3%. Possible options for ALS and ADS data aggregation and the results are shown in (Fig. 9).

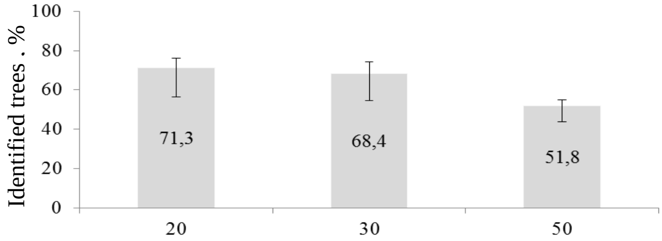

Fig. 8. **Identified trees at different pixel size. The evaluation was carried out in 10 sample plots of study area (252 trees). Plots were chosen to be structurally simple, so the proportion of second floor trees is as small as possible. Deviation intervals show the minimum and maximum values.**

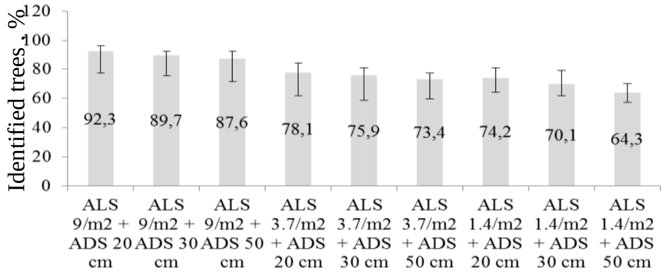

Fig. 9. **ALS and ADS data aggregation results. The evaluation was carried out in 10 sample plots of study area (252 trees). Plots were chosen to be structurally simple, so the proportion of second floor trees is as small as possible. Deviation intervals show the minimum and maximum values.**

The combined methods show better results because a part of the trees, which are not recognized by the first method, will be recognized by the other and vice versa. ADS and ALS data consolidation result is shown in (Fig.10).

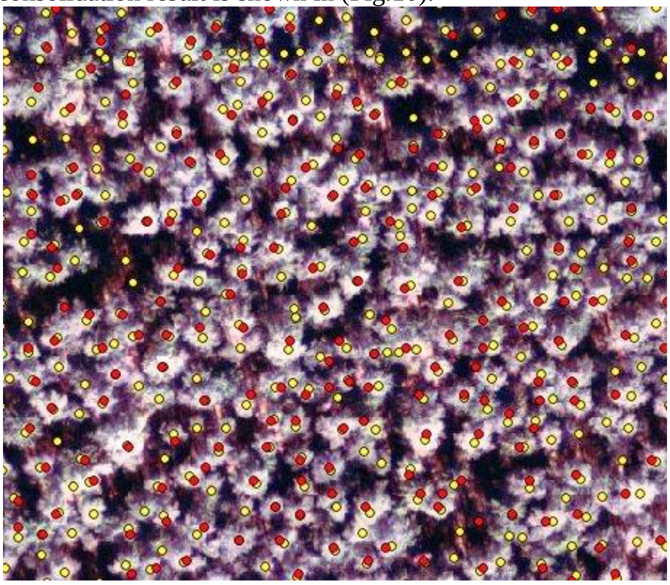

Fig. 10. **Trees identified in aggregated ALS and ADS data. The illustration shows an orthophoto of the study area. The red points show the trees identified using ALS data processing methods, and the yellow points show the trees identified using ALS data processing methods. The flight altitude was 500 m, 9 ALS and ADS p/m2 20 cm pixels in nature.**

4. Conclusion

Local maximum method with a Gaussian filter for ALS data and Fourier filter for ADS data showed the best results in practical sample plot tests and were considered the best for practical use in Latvian conditions.

Results of tree identification process can be improved by merging ALS and ADS results.

ALS and ADS data structure has a significant impact on the number of identified trees. More trees can be identified with higher resolution ADS and with a higher point density ALS data.

Latvian forest conditions are difficult for single tree remote sensing methods mainly due to mixed deciduous and coniferous spaces with high level of the second storey trees in one stand. Mostly the trees are close to each other, with high density and homogeneous crown. That is one of the main reasons for a large number of trees that are omitted.

Number of recognized trees could be improved by performing 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. Also tree crown shape analysis from LIDAR data can be used, and it means that there is a need for LIDAR data with a higher level of point density per square meter.

References

Crosilla, F., Visintini, D., Sepic, F. (2005). A segmentation procedure of LiDAR data by applying mixed parametric and nonparametric models. In: Proceedings of the ISPRS Workshop Laser scanning 2005, ISPRS Archives, Vol. 36: conference paper. Enschede (Netherlands), September 2005, p. 132-137.

Diedershagen, O., Koch, B., Weinacker, H. (2006). Automatic Estimation of Forest Inventory Parameters Based on LIDAR, Multi-spectral and Fogis Data. Department of Remote Sensing and Land Information Systems. Institute of Forestry Economics. University Freiburg, Germany, 10 p.

Edson, C. and Wing, M.G. (2011). Airborne Light Detection and Ranging (LiDAR) for Individual Tree Stem Location, Height, and Biomass Measurements. Remote Sensing, 3, pp. 2494 – 2528. http://dx.doi.org/10.3390/rs3112494

Edwards, H.G.M., de Oliveira, L.F.C., Nesbitt, M. (2002). Fourier-transform Raman characterization of brazilwood trees and substitutes. The Analyst, Vol. 128, Nr. 1, 25 November 2002, p. 82 - 87. ISSN 1364-5528 (web), ISSN 0003-2654 (print)

Heinzel, J. N., Weinacker, H., Koch, B.(2008). Full automatic detection of tree species based on delineated single tree crowns - a data fusion approach for airborne laser scanning data and aerial photographs. In: SilviLaser 2008 Proceedings: conference proceedings. Edinburgh (UK), 2008, p. 76. – 85.

Hyyppä, J., Hyyppä, H., Leckie, D. (2008). Review of Methods of Small-footprint Airborne Laser Scanning for Extracting Forest Inventory Data in Boreal Forests. International Journal of Remote Sensing, 29, pp. 339-366.

Hyyppä, J., Hyyppä, H., Litkey, P. (2004). Algorithms and Methods of Airborne Laser Scanning for Forest Measurements. Remote Sensing and Spatial Information Sciences, 36, pp. 18-25. http://dx.doi.org/10.1080/01431160701736489

Junttila, V., Kauranne, T., Leppänen, V. (2010). Estimation of Forest Stand Parameters from Airborne Laser Scanning Using Calibrated Plot Databases. Forest Science, 56, pp. 257-270.

Kane, V.R., Bakker, J.D., McGaughey, R.J., Lutz, J.A., Gersonde, R.F., Franklin, J.F. (2010). Examining conifer canopy structural complexity across forest ages and elevations with LiDAR data. Canadian Journal of Forest Research, 40, pp. 774-787. http://dx.doi.org/10.1139/X10-064

Koch, B., Heyder, U., Weinacker, H. (2006). Detection of Individual Tree Crowns in Airborne Lidar Data. Photogrammetric Engineering & Remote Sensing, 72, pp. 357–363.

Korpela, I. (2006). Incorporation of Allometry into Single-tree Remote Sensing with LIDAR and Multiple Areal Images. Department of Forest Resource Management. University of Helsinki, Finland. p. 6.

Korpela, I., Dahlin, B., Schäfe, H. (2007). Single-tree forest inventory using LIDAR and areal images for 3D treetop positioning, species recognition, height and crown widh estimation. Department of Forest Resource Management. University of Helsinki, Finland. Available at: http://www.isprs.org/proceedings/XXXVI/3-W52/final_papers/Korpela_2007.pdf , 16 January 2009.

Korpela, I., Tokola, T., Ørka, H.O., Koskinen, M. (2004). Small – Footprint Discrete – Return LiDAR in Tree Species Recognition. Environmental Sciences, 387, pp. 1381-1386.

Korpela, I. and Tokola, T.E. (2006). Potential of Aerial Image-Based Monoscopic and Multiview Single-Tree Forest Inventory: A Simulation Approach. Forest Science, 52, pp. 136-147.

Meng, H., Currit, N., Zhao, K. (2010). Ground Filtering Algorithms for Airborne LiDAR Data: A Review of Critical Issues. Remote Sensing, Vol.2, 22 March 2010, p. 833 – 860. ISSN 2072-4292 http://dx.doi.org/10.3390/rs2030833

Nicholas, R., Vaughn, L., Moskal, M. and Eric, C. (2012). Turnblom.Tree Species Detection Accuracies Using Discrete Point Lidar and Airborne Waveform Lidar. Remote Sensing. Vol. 4, 2012, p. 377-403. ISSN 2072-4292.

Onge, B., Jumelet, J., Cobello, M. (2004). Measuring Individual Tree Height Using a Combination of Stereophotogrammetry and Lidar. Canadian Jornal of Forest Research, 34, pp. 22–30.

Pitkänen, J. (2001). Individual tree detection in digital aerial images by combining locally adaptive binarization and local maxima methods. Canadian Journal of Forest Research, 31, pp. 832 – 844. http://dx.doi.org/10.1139/x01-013

Pitkänen, J., Maltamo, M., Hyyppäb, J., Yub, X. (2004). Adaptive Methods for Individual Tree Detection on Airborne Laser Based Canopy Height Model. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 36 – 8/W2, pp. 187 – 191.

Popescu, S.C., Wynne, R.H., Nelson, R.F. (2002). Estimating plot-level tree heights with lidar: local filtering with a canopy-height based variable window size. Computers and Electronics in Agriculture, Vol. 37, Nr. 1 – 3, Dec 2002, p. 71 – 95. ISSN: 0168-1699.

Pouliot, D. and King, D. (2005). Approaches for optimal automated individual tree crown detection in regenerating coniferous forests. Canadian Journal of Remote Sensing, 31, pp. 255 – 267. http://dx.doi.org/10.5589/m05-011

Rahman, M.Z.A., Gorte, B. (2008). Individual Tree Detection Based on Densities of Heigh Points of Heigh Resolution Airborne LiDAR. Available at: http://www.isprs.org/proceedings/XXXVIII/4-C1/Sessions/Session12/6790_Rahman_Proc.pdf, 4 January 2012.

Rombouts, J. (2006). Application of airbone LIDAR in forestry in North America and Scandinavia. The National Educational Trust of the Australian Forest Products Industries Fund. Australia. 2006. Available at: http://www.gottsteintrust.org/media/jrombouts.pdf, 16 January 2009.

Rossmann, J., Schluse, M., Bücken, A., Krahwinkler, P. (2007). Using Airborne Laser-Scanner-Data in Forestry Management: a Novel Approach to Single Tree Delineation. In: ISPRS Workshop on Laser Scanning 2007 and SilviLaser 2007: conference proceedings. Vol. 36, Part 3/W52. Espoo (Finland), 2007, p. 350 – 354.

Secord, J., Zakhor, (2010). A. Tree Detection in Aerial LiDAR and Image Data [online]. [s.a.] [cited 23 March 2010]. Available: http://www-video.eecs.berkeley.edu/papers/JSecord/ICIP2006_secord.pdf

Sriperumbudur, B.K., Steinwart, I. (2012). Consistency and rates for clustering with DBSCAN. In: AISTATS 2012 (International Conference on Artificial Intelligence and Statistics: conference paper. La Palma (Spain), April 2012, p. 1090 – 1098.

Tokola, T., Vauhkonen, J., Leppänen, V., Pusa, T., Mehtätalo, L., Pitkänen, J. (2008). Applied 3D Texture Features in ALS – Based Tree Species Segmentation. Available at: http://www.isprs.org/proceedings/XXXVIII/4-C1/Sessions/Session12/6724_Tokola_Proc.pdf, 4 January 2012.

Vaughn, N.R., Moskal, L.M., Turnblom, E.C. (2011). Fourier transformation of waveform Lidar for species recognition. Remote Sensing Letters, Vol. 2, Nr. 4, December 2011, p. 347 – 356. ISSN 2150-7058. http://dx.doi.org/10.1080/01431161.2010.523021

Vaughn, N.R., Moskal, L.M., Turnblom, E.C.(2012). Tree Species Detection Accuracies Using Discrete Point Lidar and Airborne Waveform Lidar. Remote Sensing, Vol. 4, Nr. 2, 2 February 2012, p. 377 – 403. ISSN 2072-4292. http://dx.doi.org/10.3390/rs4020377

Vauhkonen, J., Tokola, T., Leppänen, V. (2008). Applied 3D texture features in ALS-based tree species segmentation. University of Joensuu, Faculty of Forest Sciences. Available at: http://homepages.ucalgary.ca/~gjhay/geobia/Proceedings/Sessions/Session12/6724_Tokola_Proc.pdf , 16 January 2009.