Comparison of individual tree detection methods

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Abstract

Forests have a significant economic value in Finland and the forest industry is the only globally competitive industry branch in regional areas of Finland. Forest inventory provides the fundamental information for decision-making in the forest industry relevant to forest ecosystems. This information is usually stand-wise and can contain e.g. tree species and total volume of timber. These characteristics can be obtained by using individual tree detection.

This thesis compares three individual tree detection methods. The methods are applied to an airborne laser scanning point cloud data. The trunk detection method finds the trees directly from a point cloud by detecting vertical elongated structures. The local maxima method is based on the idea that treetops are local maxima of the canopy height model. Local maxima are detected from rasterised data. The point density method assumes that there are more laser hits on tree trunks than other parts of the trees and thus, trees can be detected from point densities.

The local maxima method had the best overall performance. It did find over 90 percent of trees with over 20 cm diameter at the breast height and 60 percent of all the trees. The trunk detection method was the most accurate, i.e. it gave least made-up trees as an output. However, it found only 17 percent of the trees. Both, local maxima method and trunk detection method, worked better for bigger trees. By contrast, the point density method's performance did not depend on a diameter at the breast height.

Keywords Forest inventory, airborne laser scanning, individual tree detection

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Tiivistelmä

Metsillä on Suomessa paljon taloudellista arvoa ja metsäteollisuus onkin ainoa kansainvälisesti kilpailukykyinen teollisuudenala Suomessa. Metsäteollisuudessa päätöksenteon apuna voidaan käyttää metsävaratietoja, jotka koostuvat muun muassa metsikköjen puulajeista ja runkojen kokonaistilavuuksista. Nämä tiedot voidaan kerätä yksinpuintulkinnan avulla.

Tässä kandidaatintyössä vertaillaan kolmea yksinpuintulkintamenetelmää. Menetelmiä sovelletaan ilmalaserkeilattuun pistepilvidataan. Runkomenetelmä etsii pistepilvestä puiden runkoihin kuuluvat pisteet ja tunnistaa näin puiden sijainnit. Runkoihin kuuluvat pisteet saavat korkeat lineaarisuus- ja vertikaalisuusarvot, jotka lasketaan pistettä ympäröivien pisteiden avulla. Maksimimenetelmä perustuu oletukseen, jossa puiden latvat löytyvät korkeusmallista paikallisten maksimien kohdalta. Pistetiheysmenetelmä olettaa, että laser osuu herkemmin runkoihin kuin muihin osiin puissa. Tällöin runkojen kohdalle syntyy pistepilvessä tihentymiä, joiden avulla voidaan saada puiden sijainnit.

Näistä kolmesta menetelmästä parhaiten suoriutui maksimimenetelmä. Se löysi yli 90 prosenttia puista, joiden halkaisija rinnan korkeudella on yli 20 senttimetriä, ja lähes 60 prosenttia kaikista puista. Kaikista tarkin menetelmä oli runkomenetelmä. Se antoi vähiten sellaisia sijainteja, joissa ei oikeasti ole puuta. Toisaalta menetelmä löysin vain 17 prosenttia puista. Runkomenetelmä ja maksimimenetelmä suorituivat molemmat paremmin isoilla puilla kuin pienillä. Pistetiheysmenetelmän suorituskykyyn taas ei vaikuttanut puun halkaisija, vaan se suoriutui tasaisesti kaiken kokoisilla puilla.

Avainsanat Metsävaratieto, ilmalaserkeilaus, yksinpuintulkinta

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1 Introduction

In Finland, about 77 percent of the land area is forest (Lier et al., 2019). Furthermore, the forests are the most significant renewable natural resource of the country. Forests have an increasing role in mitigating climate change and maintaining biodiversity. (Berg-Andersson et al., 2021)

Forests also have a significant economic value in Finland. Finland has 20 million hectares of economically-exploited forests. The volume of Finnish forest resources is 2473 million cubic meters and the corresponding annual increment is about 107 million cubic meters, out of which 75-90 million cubic meters is harvested. The Finnish forest sector accounts for significant share of export revenue and is the only globally competitive industry branch in regional areas of Finland. Finland has more than 600 000 forest owners with 2 B€ gross stumpage earnings, several thousands of harvesting companies, 1000+ transportation companies with hundreds of millions euro transportation costs and more than 1000 industrial companies with around 20 B€ total direct turnover. The Finnish forest companies are among the top forest and paper products companies in Europe. (Personal communication with Prof., Dos. Juha Hyyppä, National Land Survey of Finland)

Forest inventory provides the fundamental information for decision-making in society and forest industry relevant to forest ecosystems. In forest resource inventories stand characteristics, like stem volume, species and information about tree canopies, are necessary (Næsset et al., 2004). To obtain these characteristics one can use area-based approach (ABA) or individual tree detection (ITD). ABA can rely on calculating metrics from the point cloud collected with airborne laser scanning (ALS) (Hyyppä et al., 2017) or generalising field-measured attributes over a whole study area (Holopainen et al., 2014). When inventorying the forests at individual tree level, several benefits can be reached: Measurements of the quality of wood can be done, trees can be matched with their origin, and bucking of trees can be better predicted. As well, when forest inventory data is more accurate and updated more often, forests can serve as wood storages and the estimation of the value of forest can be improved. (Holopainen et al., 2014)

The aim of this thesis is to analyse three approaches for individual tree detection using airborne laser scanning point cloud data. The data is collected from Evo, Finland, and thus the approaches are tested in boreal forests. The algorithms will be compared to reference data and quality measures will be calculated and analysed.

In ITD the method used in calculations plays the key role in tree inventory accuracy. When ITD is done by using laser scanning data, the accuracy depends more on the ITD method than the point density of the data. Thus, it is profitable to focus on selecting the right methods rather than increasing the point density. (Hyyppä et al., 2012)

This thesis will first introduce the previous research of the individual tree detection from laser scanning data. Then the data and methods used in the ITD will be presented. Next, the results are introduced and at last there will be the discussion of the results and future prospects for ITD.

2 Previous Research

Most of the individual tree detection methods uses point cloud data as an input, and currently, laser scanning is the main technique in producing 3D point clouds (Yu et al., 2015). Laser scanning is an optical remote-sensing method based on distance and orientation between a laser scanning sensor and a reflecting object. The location of the laser scanner sensor is known either by using Global Navigation Satellite System and Inertial Measurement Unit on-board the carriage platform or by other means. Thus, with the distance and incidence angle of the measurements, obtained with laser pulse, the coordinates of the reflecting point on object (x, y, z) can be calculated. With these coordinates the forest plot can be modelled as a point cloud. (Hyyppä and Inkinen, 1999)

In airborne laser scanning (ALS) the scanner is attached to an aircraft and a point cloud is collected from above the forest. The ALS has many advantages compared to other forest inventory methods, like field inventory or aerial images. Use of the ALS results in smaller costs per hectare than field inventory when considering the information and data collecting (Kangas et al., 2019). Field inventory is also time consuming compared to the ALS. With a sufficiently accurate individual tree detection algorithm, it could be possible to provide wider forest resource information in reasonable time. Additionally, the weather and amount of light do not affect to quality of the airborne laser scanning data as it does to aerial images (Kangas et al., 2019). With the ALS one can directly measure the 3D structure of vegetation and because of that its very promising method in above-ground biomass estimations (Hyyppä et al., 2017).

First individual tree detection (ITD) method was introduced by Hyyppä and Inkinen (1999). It showed that with laser scanning it is possible to detect individual trees in boreal forest zone and thus calculate accurate stand characteristics i.e. stem volume and mean height. In this method first the point cloud was transformed into a grid. The resolution of this grid was 0.5 meters. The digital crown model (DCM) and digital terrain model (DTM) were calculated by using the highest and lowest points of the pixels in the grid. If a pixel had no points, the value was interpolated using the values of neighbouring pixels. Then by subtracting DTM from DCM a canopy height model (CHM) was obtained. CHM was filtered with low-pass filter to reduce falsely detected trees. Tree locations were obtained by looking at local maxima in CHM. After this, the tree crowns were segmented with modified watershed segmentation algorithm. (Hyyppä and Inkinen, 1999)

Many of the most recent ITD methods use the 3D structure of a point cloud instead of 2D raster grid. Kaartinen et al. (2012) states that smaller trees can be found more accurately with methods using the original point cloud than with the raster-based methods. Thus, point cloud or voxel based methods can provide better results in individual tree detection.

One point-based algorithm was introduced by Wang et al. (2016). In this method, the point cloud was normalised first using a digital terrain model. Then it was moved to a local voxel space with voxel-size of 0.5 m $\times$ 0.5 m $\times$ 0.5 m. Every voxel with at least one point inside was added to a vox-point cloud. The coordinates of a vox-point were the center coordinates of the corresponding voxel. The treetops were detected from the 3D structures of the vox-cloud with the following assumptions: There is always open space above a treetop and the treetop is a local maximum. Treetops are always supported by crowns, i.e. in the neighbourhood of every treetop there exists a cluster describing a tree crown. Last, there must be a certain 3D distance between two treetops. More detailed explanation of the tree detection procedure can be found at (Wang et al., 2016). This method outperformed its competitors in the comparison done by Wang et al. (2016). The methods were applied to point cloud with a point density of density of 8 $\frac{\text{pts}}{\text{m}^2}$. Of all the methods in the comparison, this method performed best on subordinate trees. Other point-based ITD methods can be found for example at (Hyyppä et al., 2020) and (Chen et al., 2018).

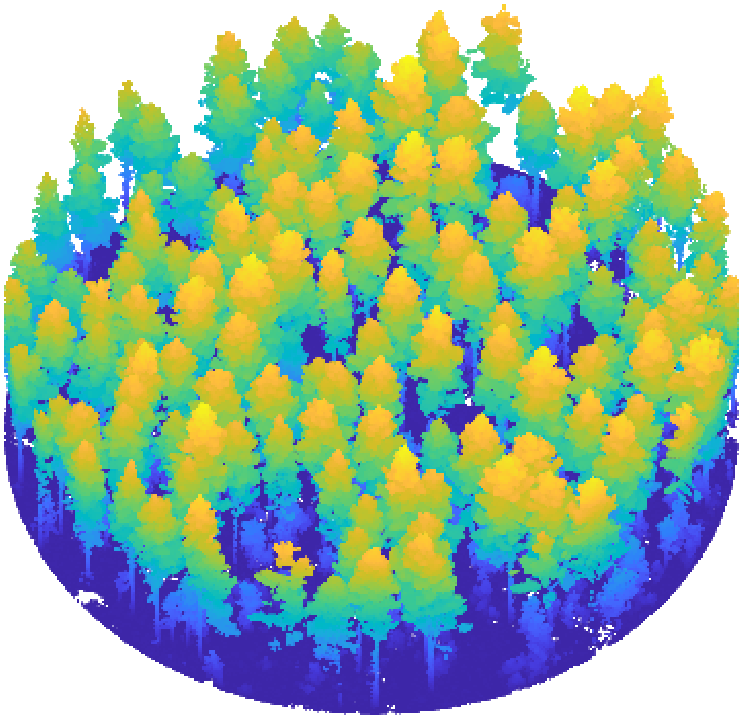

Figure 1: Airborne laser scanning point cloud

3 Data

3.1 Study area

The data was collected from Evo (61.19° N, 25.11° E) in 2014. The area is 120 km north of Helsinki and belongs to the southern Boreal Forest Zone. The elevation of the 5 km $\times$ 5 km test site varies between 125 m and 185 m above sea level. The study area consists of different kinds of forest stands, from highly managed to natural, and its dominant tree species are Scots pine, Norway spruce, and birch that are 40%, 35% , and nearly 24% of the total volume, respectively. The same test site is used in other studies like Yu et al. (2020), Kankare et al. (2015).

3.2 Field data

The study area is divided to 91 sample plots size of 32 m × 32 m. In this thesis I will be using 18 of the plots and there is up to two thousand trees in total. For each plot the reference data was collected by doing field measurements in 2014. Only the trees with bigger diameter at breast height than 5 cm were measured, with error limit of 2 mm. Tree attributes like location, tree species, diameter at breast height, crown level and height are recorded for every tree. Average values for three height (H), diameter at breast height (DBH) and volume (V) are calculated for sample plots and results are represented in Table 1.

Table 1: Descriptive statistics of field reference data

Attribute	**Min**	**Max**	**Mean**	**Standard deviation**
H (m)	1.50	36.50	14.83	6.74
DBH (cm)	4.80	64.70	14.97	9.13
V (m^3)	0.0053	4.25	0.24	0.4193

3.3 Airborne laser scanning data

The airborne laser scanning data was collected with a built-in unmanned aerial vehicle (UAV) system. The UAV-system consisted of Riegl VQ-480-U laser scanner and inertial measurement unit and it was attached to a helicopter. The scanner has a 60 degree scan angle and it uses wavelength of 1550 nm. The targeted flying speed was 50 kilometres per hour and the acquisition altitude was around 75 metres. The scanner was operated at 550 kHz point measurement height and thus, the pulse density of the laser scanning is 140 $\frac{\text{pts}}{\text{m}^2}$.

The data is stored as a point cloud where location of every reflecting point of the laser beam is recorded in xyz-coordinates. One of the point clouds is visualised in Figure 1.

4 Methods

In this study, three individual tree detection algorithms were tested using airborne laser scanning data introduced in previous section. The detected trees were matched against the field reference data. Completeness, correctness, and F-score are used as quality indicator of the tree detection. The methods were implemented in Matlab.

4.1 Local maxima method

The local maxima method was introduced in Yu et al. (2011). The method is based on a minimum curvature-based region detector. It segments the tree crowns from canopy height model and during this process the locations of the individual trees are determined. Following procedure is used to detect the trees: First a raster canopy height model (CHM) is constructed from normalised data. To remove small variation that could induce false results, the CHM is smoothed with a Gaussian filter. Then minimum curvature value is calculated for each raster cell. Minimum curvature is one of the two principal curvatures and it measures the bending of the surface. Higher values of minimum curvature in CHM describes the tree tops and lower values the areas between the trees. After these calculations, the CHM is contrast-stretched in respect of minimum curvature values. Local maxima are then searched from this newly scaled image and they are considered as treetops.

4.2 Trunk detection method

The trunk detection method was developed by Matti Lehtomäki (National Land Survey of Finland) and it has not been published yet. The method finds the trees directly from the point cloud using the fact that trunks are usually vertical elongated structures. The algorithm calculates linearity and verticality values for each point and compares them to threshold values given as an input. If the values exceed the threshold, the point is considered to be part of the trunk. Trunk points with a sufficiently small horizontal distance from each other are considered to belong to the same tree. From these clusters the tree locations are calculated. The method uses function called edgesKNNgraph.m that is based on function introduced by Wang (2020). Trunk detection method works best for trees where there are not many branches and the trunk is well visible, e.g. Scots pines.

4.3 Point density method

The point density method is modified from Valtteri Soininen's tree detection method based on finding local maxima. The method assumes that there are more laser hits on the trunks than elsewhere and thus, the trees can be detected from point densities. First, a grid is formed in which the value of each pixel is the number of points in it. Then, the grid is smoothed using a Gaussian filtering and the local maxima are detected. These local maxima are seen as treetops. The accurate tree location is the location of the highest point in the pixel.

4.4 Evaluation of accuracy

After the algorithm is used to detect the individual trees from point cloud, the founded trees are matched to field-measured trees using a method based on the

Hausdorff distance. The Hausdorff distance is defined as

$$h(A,B) = \max_{a \in A} \left\{ \min_{b \in B} \{d(a,b)\} \right\}, \tag{1}$$

where A and B are two point sets and a and b points belonging to them, respectively, and $d(a,b)$ is any metric between points a and b. In this case, the Euclidean distance is used. It measures how close the points of the one set are to some point of the other set. Hausdorff distance is asymmetric and therefore $h(A,b)$ is not necessarily $h(B,A)$. First are calculated the distances from the laser scanned trees to the field measured trees, where every tree can be seen as a point in a point set. Then the distances are calculated from the field-measured trees to laser scanned trees. Trees closest to each other are matched. (Yu et al., 2006)

To evaluate the accuracy of different individual tree detection methods we will calculate correctness, completeness and F-score. These measures are got by comparing trees in reference data to the trees found with the algorithm. The completeness (omission) represents the tree detection rate i.e. how many of the actual trees is found and correctness (commission) tells if the detected trees are found also from the reference data. F-score takes both omission and commission errors to a account (Goutte and Gaussier, 2005). The values for these tree measures vary from 0 to 1. If F-score is one the trees were detected without any errors and if the value is zero none of the actual trees were found.

The measures are calculated with following formulas (Li et al., 2012):

$$completeness = \frac{N_t}{N_t + N_o} \tag{2}$$

$$correctness = \frac{N_t}{N_t + N_c} \tag{3}$$

$$F_1 = 2 \cdot \frac{completeness \cdot correctness}{completeness + correctness} \tag{4}$$

where N_t is the number of the correctly matched trees and N_o and N_c are the omission and commission errors, respectively.

5 Results and discussion

Indicators measuring the goodness of the ITD methods were calculated to all 18 plots and the mean values are represented in Table 2. The completeness is also calculated for trees with different DBHs that are shown in Table 3.

Table 2: Means of the quality measures

Method \ Statistic	Completeness	Correctness	F-score
Local Maxima	0.5740	0.6555	0.5861
Trunk Detection	0.1700	0.9658	0.2731
Point Density	0.3226	0.6905	0.4205

Table 3: Completeness for different tree sizes

Method \ DBH	5-20 cm	20-40 cm	> 40 cm
Local Maxima	0.3970	0.9194	0.9597
Trunk Detection	0.1208	0.1935	0.3166
Point Density	0.3118	0.3775	0.3488

Local maxima method got the biggest f-score and completeness of all tree methods. As it can be seen in Table 3, local maxima method works very well for trees with DBH bigger than 20 cm: it found over 90% of those trees.

Trunk detection method was very accurate. It got correctness value of over 0.95, so it gave almost no made-up trees as output. The method detected larger trees notably better than smaller ones. Trunk detection method did not get good completeness values: it detected only 17% of the trees. However, with denser point cloud there would be more trunk hits and thus, the method could detect a bigger share of the trees.

Point density method got a little bit bigger correctness value as local maxima method but it did find less trees. So, its overall performance was not as good. Unlike other methods, point density method performed relatively similarly regardless of the DBH. This method, as well, could work better with higher point density because of the increasing number of trunk hits.

In summary, local maxima method had the best overall performance with the highest f-score value. Trunk detection method was the most accurate. Both, point density method and trunk detection method, would probably work better with denser point cloud.

In the future research it might be worthwhile to try to combine existing methods to achieve better and more accurate results in individual tree detection. For example, canopy can be shaped so that there is no clear maximum at the treetop in the canopy height model. Despite this, there can be high point density at the trunk and thus, the tree could be seen from the density model. Therefore, combination of local maxima method and density method might lead to better results.

Future research should also combine raster, voxel and point cloud based approaches where it is possible to process the same tree computationally effectively with these different data structures. For example, 2D raster data is expected to be beneficial for finding dominant trees. Voxel approach may be beneficial for discriminating co-dominant trees from dominant trees together with pulse mode information, and point clouds based approaches should suit for finding suppressed trees and trees in the intermediate layer. Using the last pulse data, an improvement of 6% for individual tree detection was obtained in Hyyppä et al. (2012) when compared to using the first pulse data since it was easier to distinguish near-by trees with pulses penetrating more to the foliage than those coming from tree tops. The improvement increased with decreasing diameter breast height. The methods was based on two-dimensional CHMs.

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