SINGLE TREE DELINEATION USING AIRBORNE LIDAR DATA

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Abstract

In this paper, single tree extraction was carried out using the first and last pulse airborne LIght Detection And Ranging (LIDAR) data. The LIDAR data was collected from TopoSys in May 2007 in the Milicz forest district, Poland, with a density of 7 points m^{-2}. The total study area contains 25 circular plots of different radius according to the age of the trees. The absolute height of each point was obtained by normalizing the LIDAR raw data points using a digital terrain model (DTM) of the area. The value of σ used while smoothing was found higher for the deciduous tree dominating plots as compared to the coniferous plots. A modified *k*-means clustering algorithm was applied to extract the clusters of single tree above 4m height in each plot from the normalized LIDAR point clouds. 3-D convex polytope reconstruction from the extracted clusters of each tree was carried out using QHull algorithm. The validated result shows that an average of nearly 86% of the matured deciduous and 93% of the matured coniferous trees were extracted by the presented approach. Almost equal average accuracies were obtained in the case of young deciduous and coniferous tree species (58%). It seems that the algorithm did not work well with relatively younger tree types even after varying the parameters at pre-processing steps. The study showed that the adjustment of certain parameters like threshold distance, smoothing factor and scaling factor for the height before initialising the main process, has a substantial impact on the number and shape of the trees to be extracted

more appropriately by applying the modified *k*-means procedure. There is a future scope of improving and testing the algorithm with different density of LIDAR data in different forest conditions.

Keywords: Lidar, forestry, segmentation, clustering, delineation

1. Introduction

In the past decade the demand of airborne LIght Detection And Ranging (LIDAR) data with high quality (e.g. optimal footprint size, high point density) and more information (intensity, pulse width, number of echoes from each emitted laser pulse) has increased for various applications. Some of the LIDAR based applications of interest are the estimation of biophysical parameters in forest management performance using different techniques (Woodget *et al.* 2007, Suárez *et al.* 2008, Maltamo *et al.* 2009, Ørka *et al.* 2009a) and environmental planning practices (Nilsson 1996, Hudak *et al.* 2008, Tooke *et al.* 2009). The increasing demands of single tree extraction, as a basis to improve the forest management performance, is the motivating factor for developing various methodologies for single tree extraction from airborne laser scanner (ALS) data. The term 'single tree' includes the term 'single tree crown' throughout the paper because of the difficulty in delineating the whole tree. Clustering algorithms provide a good way of partitioning the complete normalized ALS dataset of the test area into an individual cluster (e.g. tree in a forested test site). Through this mechanism, the 3-D geometric feature spaces are divided into individual clusters containing point values similar to each other using a squared Euclidean or any other distance matrix. There are several clustering mechanisms, for example, the hierarchical tree clustering, the *k*-means and the fuzzy C-means (FCM). In this study, the most popular *k*-means was chosen, which is an iterative hill-climbing approach and a staple of clustering methods. In contrast to the hierarchical clustering based approach, the *k*-means uses the actual observations of the objects and not just their proximities (Gupta *et al.* 2010). In the hierarchical clustering, the tree is not a single set of clusters unlike the *k*-means, but rather a multilevel hierarchy. The FCM is one of the promising alternative approaches for cluster analysis. Few works on FCM have been done for image data (Dulyakarn and Rangsanseri 2001, Chen *et al.* 2005).

Various studies on the application of airborne LIDAR data for vegetation related information retrieval have been conducted in the past by using different methods (Hyyppä *et al.* 2006, Persson *et al.* 2006, Wang *et al.* 2008a, Wang *et al.* 2008b, Ko *et al.* 2009, Vauhkonen *et al.* 2009). There are two main approaches in extracting forest information from LIDAR data: the canopy height distribution-based and the individual tree detection-based approaches (Maltamo *et al.* 2006). For the single tree delineation, the major existing algorithms are the digital surface model (DSM) or the normalized DSM (nDSM) based, which are the result of a surface interpolation (Hyyppä and Inkinen 1999, Persson *et al.* 2002, Koch *et al.* 2006, Rossmann *et al.* 2007). The main drawback is that the trees and young regeneration in the intermediate and lower forest layers are invisible from the nDSM surface and hence cannot be detected at all (Reitberger *et al.* 2008a, Reitberger *et al.* 2009). Wang *et al.* (2008a) presented a new method for 3-D single tree crown contour extraction at different height level using a hierarchical morphological process. In their study, they have suggested to use the pre-knowledge of the stand situation in their algorithm to control the input variables. Wang *et al.* (2008b) tried to find out better results by modifying the horizontal and vertical space of the voxel space and the crown growing radius for different forest types, but they still found considerable failures in the individual tree detection. Reitberger *et al.* (2008a) showed that the new full waveform LIDAR data significantly improves the detection rate of single trees using a 3D segmentation technique based on the normalized cut segmentation method using variable LIDAR point density (10 and 25 points m^{-2}). The high point density from the full waveform data (25 points m^{-2}) was the key factor to segment the dominant trees in the upper canopy layer as well as the dominated smaller trees in the lower and intermediate layers in 3-D using normalized cut method (Reitberger *et al.* 2009). However, the increased detection rate also deteriorates the reliability of the segmentation process by the factor 2 in terms of false positives (Reitberger *et al.* 2008a). If the density of laser pulses is increased per square meter, the probability of individual trees detection is increased (Maltamo *et al.* 2006). Several studies have been performed in the past by using the local maxima to find out the tree top locations, majority in the image domain and fewer in the vector domain. A pixel counts as a local maximum, if all of its neighbours have got a lower height-value or if all the neighbours of some connected pixels with equal height (a “plateau”) have got a lower height value (Koch *et al.* 2006). In tree detection on a nDSM, local adaptation has been done at least by adjusting the window size used for finding local maxima (Popescu *et al.* 2002) and by choosing different scales, produced by Gaussian filtering, in the different parts of the image (Persson *et al.* 2002). Popescu *et al.* (2002) estimated the plot level tree heights with LIDAR data based on the local filtering with a canopy height-based variable window size. In the study conducted by Pitkänen *et al.* (2004), the first-pulse LIDAR derived nDSM was smoothed with canopy height based selection of degree of smoothing. The local maxima on the smoothed nDSM were considered as tree locations (Pitkänen *et al.* 2004). An approach to delineate single tree crowns automatically using the first and last pulse LIDAR data in the deciduous and mixed temperate forests of Germany was presented by Koch *et al.* (2006). The tree tops were detected with a local maxima filter in the nDSM. Afterwards, the tree crowns as regions were delineated with a combination of a pouring algorithm, knowledge-based assumptions on the shape of trees, and a final detection of the crown-edges by searching vectors starting from the trees tops. Based on the assumption that the tree tops have a certain minimal distance from each other, they chose 1m for the trees below 22m and 2m for the trees above 22m. If the two tree tops were within this distance, the corresponding crown segments were merged using the segmentation algorithm (Koch *et al.* 2006). In the study conducted by Tiede *et al.* (2008), a supervised approach for the process of segmentation and the object generation utilising human a *priori* knowledge on the specific scale domain of the target features has been presented. Tiede and Hoffmann (2006) have developed specific rule sets for the single tree crown delineation using the first and last pulse ALS data, which was later adapted (Tiede *et al.* 2008) to the specific conditions in the study areas and the data sets used. In their rule sets, a region growing segmentation algorithm was programmed using a continuity constraint starting from the tree tops (local maxima) as seed points.

A method for delineating crowns from the raw first return ALS data using Delaunay triangles and Voronoi polygons in a vector environment for a Finnish test site was presented by Cici (2009). The seed points were identified at three different scales based on the elevation value (Cici 2009). In this case, the seed points were the local maxima at their scale and considered directly as the tree tops. The accuracy was largely scale-dependent and the algorithm needs to be tested in different forest conditions with different datasets (Cici 2009). Single tree extraction by applying clustering based approaches with airborne LIDAR data has been carried out in the past (Morsdorf *et al.* 2003, Morsdorf *et al.* 2004, Doo-Ahn *et al.* 2008, Cici *et al.* 2008, Reitberger *et al.* 2008b). Morsdorf *et al.* (2003) used the first and last pulse data with an overall density of 30 points m^{-2} and the *k*-means method to extract single trees in the Swiss National Park. They used local maxima derived from the smoothened DSM as the seed points. In contrast to the algorithm used in the presented approach, instead of scaling-down the z-coordinate value, they scaled it up by three. They argued for it that they did it to accommodate the aspect ratio of pine tree crowns, which ranged in between 3-6. Riaño *et al.* (2004) estimated a derivative of foliage biomass, the crown bulk density, using LIDAR metrics with the *k*-means clustering at both plot and individual tree scales. The individual tree level analyses were not completely successful in their work. Ko *et al.* (2009) have shown in their paper deciduous-coniferous classification using the single leaf-on Riegl LMS-Q560 /LMS Q280i full waveform data of high point density (21 points m^{-2}). They separated 65 individual tree crowns manually from the LIDAR data and characterised the tree crown shape by comparing the crown of real LIDAR tree point clouds to artificially generated point clouds by the Lindenmayer system language. They applied simple *k*-means clustering for deriving the branches of 27 coniferous and 38 deciduous trees for improved visualisation. They also calculated the volume and surface area of the convex hull reconstructed from each tree crown clusters. Nevertheless, in their study the result was not validated using any field data. Ørka *et al.* (2009b) tested supervised classification strategy using linear discriminant analysis (LDA), random forest (RF) algorithm and support vector machines (SVM) for the tree species classification. They also used unsupervised *k*-means clustering and the *k*-means clustering in combination with the unsupervised RF algorithm for the same objective. Their result showed that the accuracies were lower in the case of unsupervised methods than for the supervised ones applied to overall tree species classification. However, in the study conducted by Reitberger *et al.* (2008a), almost equal accuracies were obtained with unsupervised (Expectation-Maximization algorithm) and supervised (maximum likelihood classification) methods. They used different datasets (first and last pulse and full waveform) of different point densities in the leaf-on and leaf-off seasons. Their result showed that the classification accuracy decreases slightly for the lower and intermediate layers in the leaf-on case. This work explicitly differs from the previous work done by Gupta *et al.* (2010) in way a that the previous work was a comparative study of the two clustering mechanisms viz. k-means and hierarchical clustering mechanism in their varied forms, without any quantitative.

The shape of the tree crowns using the vector data are shown in different forms and relate approximately to the geometry of the actual tree crown when examined visually. There are many ways for constructing the shape of the extracted LIDAR point cloud of a single tree using different computational geometry concepts like convex hull, 3D Delaunay triangulation. The individual cluster can also be shown as 3-D surface or in the form of a mesh. Vauhkonen *et al.* (2009) used linear discriminant analysis for the classification of individual trees and alpha shape metrics for tree species classification (pine, spruce, and deciduous trees) in Scandinavian test sites comprising 92 dominant or co-dominant trees detected and delineated manually from a very dense ALS data (40 points m^{-2}). The method applied required to be tested for larger datasets with varying point density.

The objective of this paper is to examine the potential of the modified *k*-means algorithm for single tree extraction using ALS data, the validation of the result obtained with that of the field data, and the shape determination of the extracted tree clusters in 3-D using QHull algorithm.

2. Materials and Methodology

2.1. Study area and field data characteristics

Investigations were carried out in the Milicz forest district, State Forestry Regional Management in Wrocław, Poland. This was done by the Faculty of Forestry, Warsaw University of Life Sciences, Warsaw, Poland. The Milicz forest district comprises 26 250ha, of which, 96% (25 362ha) is covered by the forest. The dominant tree types are Scots pine (*Pinus sylvestris* – 76%), Oak (*Quercus sp.* – 9%), European Beech (*Fagus sylvatica* – 4.7%), Alder (*Alnus glutinosa* - 4.5%) and 5.8% others species (Birch - *Betula pendula*, Norway spruce - *Picea abies*, European larch - *Larix decidua*, Hornbeam - *Carpinus betulus* and few minor species). The plots containing coniferous trees (mainly Scots pine) are mostly made up of single canopy layer. From the field-inventoried data, the age of the trees in the forested area varies between five to greater than 100 years and that of analyzed plots with different dominant species, varies between 26 and 152 years. The average stand volume is 290 m^3 ha^{-1}. Generally, flat relief covers the study area, except in a plot no. 3, with occasional sand dunes. Figure 1 shows the location of the study area.

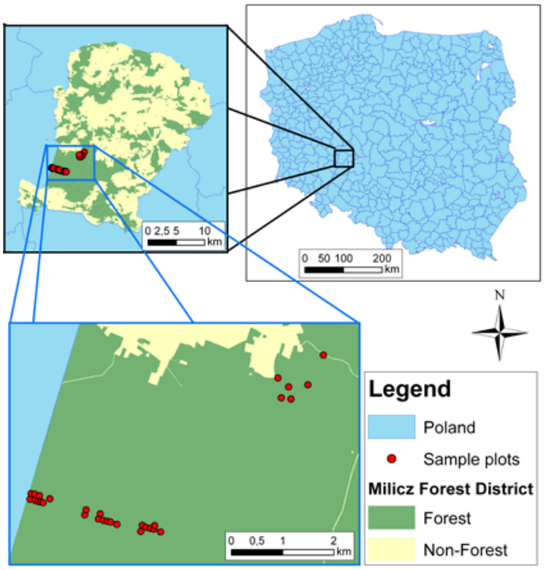


Figure 1. Location of plots within the Milicz Forest District, Poland.

The forest inventory was carried out in autumn 2006 covering 30 sample plots. The radius and size of the sample plot depend upon the age of the stand (Rosa 1977) as presented in table 1. In this study, the projected size of the sample plots is similar to the size of the plots used in the Polish Operational Forest Inventory (Bruchwald and Zajączkowski 2002), where they have applied the prism inventory method using “variable radius” plots. Each tree has a different “plot” radius - larger trees have larger plots. The adjustment was necessary in order to compare the results from both traditional and remote sensing methods. The radius of the sample plots changes with the age as it is correlated with the tree density and the tree trunk Diameter at Breast Height (DBH). Due to the changing plot size, more than 20 trees were measured in each sample plot. It was also necessary to avoid micro-variation in cross-section breast-height stand area or basal area, which is the base for the average stand volume calculations.

Age (years)	**Radius (m)**	**Plot size (ha)**
21 – 30	3.99	0.005
31 – 40	5.64	0.01
41 – 60	7.98	0.02
61 – 80	9.77	0.03
81 – 100	11.28	0.04
> 100	12.62	0.05

Table 1. Age of the stand, radius of the plot and total area of 25 plots in each age class.

Thirty plots were measured (as a reference for terrestrial and airborne LIDAR measurements) using the geodetic method (coordinates of centre point of each plot using DGPS). Other recorded parameters were azimuth and distance from the middle point of each sample plot to each tree inside the plot, the DBH of all trees (using diameter tape), the height of all trees from different layers (separately for each species using Suunto clinometer) and the position of each tree trunk coordinates. The tree coordinates were derived using the azimuth and distance from the centre point of each plot using Suunto compass and tape.

A comparison was initially made between the field measured data (vector layers) and the LIDAR data that showed that one sample plot had been harvested before the laser scanning was carried out. In four out of 29 remaining sample plots, it was not possible to connect single trees from the field measurements with the corresponding trees on the DSM and orthophoto. Therefore, five sample plots were excluded from the further analysis and the study was focused on the remaining 25 sample plots. Table 1 shows the correlation of the average age of the plot and the radius of the circular plot with the total area of the plots in each age class. It is important to note that the radius of the plot can be modified if it lies on undulating terrain. For example, the radius of the plot no. 3 (dominated by the matured European beech), whose slope was 9%, was modified from 12.62 to 12.71m.

2.2. First and last pulse airborne LIDAR data and preprocessing

For the individual tree extraction, the first and last pulse ALS data were captured by TopoSys (Falcon II System) on 2-3 May, 2007, with a scanner on flight of altitude 700m above ground level at the wavelength of 1560nm, a scan angle of 14.3° degrees (±7°) and a 70cm footprint size of the laser beam. There is a strong irregularity in the pattern of the collected LIDAR raw data points with the point density for the first and last echo being 7 m^{-2}.

Earlier investigations made by W Zakładzie Systemów Informacji Przestrzennej i Geodezji Leśnej (ZSIPiGL), Faculty of Forestry, Warsaw Agricultural University, Warsaw, Poland, showed that the field data matched with that of the LIDAR point data (Wang *et al.* 2008b). The vector data (tree position, tree height, DBH) were acquired at ground level. The vector data were some time not very accurate due to different accuracy level of two different Global Positioning System (GPS) instruments used during the flight and ground measurements, respectively. In such case, nDSM and orthophoto were used to distinguish the neighbouring trees in the upper canopy layer. Once the trees were identified correctly both on the nDSM and orthophoto, the data from 25 sample plots were merged with 100% certainty between the field measurements and their correspondent nDSM (Wang *et al.* 2008b) of 0.5m resolution.

2.3. Orthophoto characteristics

RGB and CIR true-orthophoto were based on the images collected during spring (April-May) 2007 with the TopoSys line scanner, at 700m above ground level. DSM from LIDAR data is a base for true-orthophoto calculation or the orthorectification. The recorded LIDAR data was combined with the recorded DSM and for each recorded "pixel" the position in the DSM was calculated. The orthorectification of the images using the DSM was carried out strip by strip. In a next step these single strips were patched together with contrast and brightness balancing. Finally, the whole patched area was cut down into tiles and resampled in to 8-bit true-orthophoto with the spatial resolution of 25cm.

2.4 Data processing

All the data processing works were carried out in a 100m by 100m area in each of the 25 circular plots. Subsequently, for accuracy assessment, the data were clipped to the plot size. This was done to include those reference tree crowns and tree top points, which were intersected at the edge and/or were found outside the circular plot.

The raster Digital Terrain Model (DTM) and DSM of 0.5m resolution were calculated from the raw LIDAR point clouds in the TreesVis environment. The TreesVis is software for LIDAR data visualisation and analysis developed by the Department of Remote Sensing and Landscape Information Systems, Albert-Ludwigs University, Freiburg, Germany (Weinacker *et al.* 2004). The nDSM was generated by subtracting the height values of the DTM from the corresponding DSM in the TreesVis. Filtering and interpolation of the raw LIDAR data were performed using an 'Active Contour Algorithm' implemented in the TreesVis software (Weinacker *et al.* 2004). The DSM, DTM and nDSM images were used as an input for various preprocessing steps viz. normalization of the raw LIDAR points, generating the boundary of each plot as a region and extracting the local maxima above 5m height. The raw LIDAR points were normalized using the DTM to ensure the absolute height of the object and to eliminate the influence of the terrain. The obtained normalized LIDAR data were then used in the main process for clustering.

Clustering by Modified k-means

The *k*-means is a numerical, unsupervised and non-deterministic method. The *k*-means treats each observation in the input data as an object having a location in the space. It is also advantageous to implement *k*-means since it uses the actual observations of the objects (rather than the larger set of dissimilarity measures), and not just their proximities unlike the hierarchical clustering based approaches. The objective of the *k*-means method is to minimise the total intra-cluster variance or the squared error function. In this algorithm, the sum of absolute differences between each point and its closest centre in Euclidian 3-D space is minimised. Each centroid is the mean of the points in that cluster. This objective can be expressed in the following 'equation (1)':

$$D = \sum_{i=1}^{k} \sum_{x_i \in C_k} \left| x_i - C_j \right|^2 \qquad (1)$$

where, there are k clusters C_k with iterations i beginning from 1 to k, D is the total intra-cluster variance or the squared error function, x_i is the data point (vector data) and C_j is the mean vector or cluster centre.

The minimum computational complexity of the *k*-means algorithm is O(ndcT) where n is the number of d-dimensional pattern, d is the number of feature vectors, c is the number of assigned clusters and T is the number of iterations.

The *k*-means algorithm was supervised to use the local maxima as external seed points to initialise the iteration, instead of selecting it randomly by the user. This was done because finding the pattern of individual trees in natural forest conditions is very difficult by selecting *k* clusters randomly using the normal *k*-means algorithm. To avoid trial and error approach with several repetitions and cross-checking each time visually with reference data in order to choose an appropriate *k* clusters for each plot, the normal *k*-means algorithm, thus, was modified. The performance of the algorithm was improved by reducing the height value of data points and the external seed points to half. The logic behind this reduction of height is that it brings the normalized raw points as well as the local maxima points to be used as seed points closer 'height-wise' and minimise the intra-cluster variance, which is the ultimate objective of the *k*-means algorithm. The reduction of the height to half was found empirically with trial and error based approach and has been kept constant for all the 25 plots investigated. This was in contrast to the work presented by Morsdorf *et al.* (2003) in which they also used the local maxima as seed points. In contrast to the algorithm presented in this paper, they scaled-up the z-coordinate by three to accommodate the aspect ratio of pine tree crowns, which ranged between 3-6 based on the field data. On the contrary, in a previous study conducted by Gupta *et al.* (2010), it was concluded that by scaling down the height value of the normalized raw points as well as seed points 'height-wise' in the space helps in minimising the intra-cluster variance or the squared error function. The closer the points will be, more precise will be the cluster formation with regard to the actual tree/tree crown and its shape. Additionally, this study differs from Morsdorf *et al.* (2003) in a way that the unwanted local maxima points were deleted by search criteria using a threshold distance in the pre-processing step as highlighted below.

Extraction of local maxima and weeding out the unwanted local maxima points using a semi-automatic approach

The local maxima points were extracted from the nDSM image above 5m height having a grey value larger than the grey value of all its 8 neighbours. Before extracting the local maxima, a gentle discrete Gaussian smoothing was performed on the nDSM image. After extraction, the local maxima points were projected over the true-orthophoto for visual check. It was observed that the number of extracted local maxima points were too high. For seeding purpose, this simply means that a higher number of single trees will be extracted after running the algorithm. In the next step, the seed points that were too close to each other were excluded based on the search criteria using the threshold distance. The filtered local maxima were finally used as external seed points in the modified *k*-means algorithm. The threshold distance, varied depending on the forest conditions. For example, the plot that holds mainly older trees requires higher threshold distance because local maxima from smaller peaks will most likely represent only branches, hence needs to be eliminated. Since, the local maxima from a peak in a plot containing younger trees will most likely to be a tree top, it requires comparatively smaller threshold distance. The value of the threshold distance for filtering the local maxima (obtained after very gentle smoothing) with younger trees of single and narrow crown at the tree top or conifer was found between 2-3m. While the threshold distance for filtering the local maxima (obtained after gentle to moderate smoothing) of relatively older trees with wider crown and more intermittent peaks at the tree top was found between 2-5m. The search and exclusion process was carried out as follows:

(a) Set the threshold distance (d_{thres}), for each plot (to filter out the local maxima points above it and to avoid multiple local maxima from single trees)
(b) Set $i = 1$
(c) Calculate the Euclidean distance $D(i,j)$ of each local maxima point p_i with reference to all remaining local maxima points L_j as expressed in the following 'equation (2)':

$$D(i,j) = \sum_{i=1}^{n} \sum_{p_i \in L_n} \left| p_i - L_j \right|^2 \quad (2)$$

where, there are n local maxima points L_n from 1 to n. $D(i,j)$ is the inter-point Euclidean distance, p_i is the local maximum point and L_j is the remaining local maxima points.

(d) if, $D(i,j) \geq d_{thres}$, select the local maxima point p_i and assign it to L_j,
else, reject p_i
(e) Increment $i = i{+}{+}$ and update the L_j to get a new set $L_1(i)$, $L_2(i)$, ...,$L_n(i)$
(f) Repeat steps (b) to (e) until $L_n(i) = L_n(i + 1)$ for all n

The Gaussian smoothing of the nDSM levels out minor height deviations. In addition, small trees or branches might be also lost, if the image is strongly smoothened. In order to minimise such effects, the intensity of smoothing was adapted to the height of the trees (Koch *et al.* 2006). In a height based filtering method applied by Pitkänen *et al.* (2004) for single tree detection on the nDSM, five Gaussian kernels were used so that the kernel size increased along the height of pixel being smoothed causing the increase in smoothing. They have selected the smallest and largest σ values by looking visually for finding the optimum number of local maxima that fit in to the selected tree height range. The height ranges and corresponding σ values used by Pitkänen *et al.* (2004) were 0-6m σ 0.4; 6-14m σ 0.6; 14-22m σ 0.8; 22-30m σ 1.0 and over 30m σ 1.2. Koch *et al.* (2006) divided the nDSM into two height classes, below and above 20m height, respectively. Each height class was filtered separately with a Gaussian function (σ = 0.81 for trees below 20m and σ = 2.0 for trees above 20m), and both parts were merged afterwards. In their study, the optimal number of height classes, the height-threshold, and the smoothing intensity have been determined in pre-tests for the presented data by visual judgment of preliminary segmentation results.

In the presented study, the σ value considered for the three European beech dominating plots was in the range of 1.3-1.4. The mean height value (H_{mean}) of the European beech ranged between 30-34m. The σ value used for each of the Oak and Hornbeam dominating plots were 1.0 and 0.9, respectively. The H_{mean} of each Oak and Hornbeam dominating plots were 31m and 22m, respectively. The value of σ used for the 20 Scots pine dominating plots were in the range of 0.6-0.8. Among the 20 Scots pine plots, the H_{mean} ranged between 12-24m (majority above 17m). The value of σ was lowered in coniferous tree species compared to the deciduous tree species because of their crown width.

According to Tiede *et al.* (2006) search radius, a region-specific parameter, for the local maximum was controlled according to the tree type, tree height and tree density in their tree crown delineation algorithm (varied between 1-4m). The search radius was adapted for each region depending on the assigned domain, for e.g. taller deciduous trees require a bigger search radius to avoid detecting false positives due to the flat and wide crown structure while the dense coniferous stands require a smaller search radius to detect close standing tree tops. Their study differs from the modified *k*-means approach presented in a way that they further used the region-growing algorithm on the nDSM using set criteria for delineating single tree crown, e.g. maximum crown width and difference in height between different objects which, in turn, depend on the tree height and the tree type. The crown width, used as a *priori* knowledge, was directly linked to the individual tree height value derived from the ALS data (Pitkänen *et al.* 2004, Koch *et al.* 2006, Tiede *et al.* 2008). According to Maltamo *et al.* (2004) and Pitkänen (2001) the local maxima method is mainly suited to find dominant trees. In the presented study, this was not validated because of homogeneity in the tree height and tree type in most of the studied plots. Thus, the height and tree type specific σ value for smoothing of nDSM image and d_{thres} for the removal of unwanted seed points are important user controlled and forest dependable variables in the presented approach.

Modified k-means algorithm

The modified *k*-means algorithm applied to a set of n-dimensional vectors (here, 3-D vector points) works as follows:

(a) Scale down the height value of the external seed points and that of the data points by half before initialising the iterative partitioning process

(b) Set $i = 1$

(c) Select external seed points as a set of k means $C_1(1)$, C_2 (1), ...,$C_k(1)$ where i = 1 in this case (mean vector for each cluster centre)
(d) For each vector x_i, begin computation D (x_i, $C_k(i)$, for each i = 1, ..., k) and assign x_i to the cluster C_j with the nearest Euclidian distance in 3-D space (means)
(e) $i = i$++ and update the means (C_j) to get a new set $C_1(i)$, C_2 (i), ...,$C_k(i)$
(f) Repeat steps (b) to (e) until $C_k(i) = C_k(i + 1)$ for all k
(g) Scale up the height value of the seed points and clustered data points to its original

2.5. 3-D Reconstruction of Individual tree clusters

The tree crowns are abundantly found in convex shape. Therefore, the shape reconstruction of the extracted tree requires a different method. The geometrical reconstruction of each delineated tree cluster was done using the QHull approach (Barber *et al.* 1996). QHull is a general dimension code for computing convex hulls using Quickhull algorithm (Berg *et al.* 1997). Each tree crown cluster was constructed with triangular surface as a 3-D convex polytope. Those clusters whose polytopes could not be formed were discarded.

The convex hull of a set of points is the smallest convex set containing those points. O'Rourke (1994) has given the detailed introduction with example codes. QHull can be used if the surface is convex or completely visible from an interior point. It projects each site to a sphere that is centered at the interior point, and then computes the convex hull of the projected sites. The facets of the convex hull correspond to a triangulation of the surface. This algorithm combines the 2-d Quickhull algorithm with the n-d beneath-beyond algorithm (Preparata and Shamos 1985). The main advantages of Quickhull are its output of performance sensitivity (in terms of the number of extreme points), reduced space requirements, and floating-point error handling. Therefore, each tree crown can be depicted as a 3-D object with a triangular surface in the case of 3-D convex polytope.

2.6. Validation method

After the careful consideration of available informations, an evaluation procedure has been devised and presented in this study. The related approaches to validate the detected tree tops has been presented by the authors (Persson *et al*. 2002, Heurich *et al.* 2004, Koch *et al.* 2006, Wang *et al.* 2008b, Koch *et al.* 2009, Reitberger *et al.* 2009). For the accuracy assessment of automatically detected tree tops with reference to field measured tree tops, four major validation classes have been adopted. In addition, two more classes (Ignored and Error) were included because of their significant role in the accuracy assessment.

- Exact - only one automatically detected tree top within a reference tree crown, the distance between the reference tree top and the detected tree top points is ≤ 3m
- Nearly Exact - one automatically detected tree top nearly at the same height level nearby a reference tree crown (may fall outside of the crown as well). The distance between the reference tree top and the automatically detected tree top points is between 3-5m
- Gap - there is no automatically detected tree top inside or nearby the reference tree crown
- Doubtful - doubtful quality of the reference tree tops, but correct detected tree tops. This was found after the visual inspection of the tree tops using the nDSM and orthophoto. Some of the examples in this case are: a reference tree top point outside the edge of the crown and plot, two tree tops up to the 3-5m distance apart to each other, which are sometimes measured from the ground as a single tree and the position of the reference tree top shifted from the detected one
- Ignored - more detected tree tops than the reference tree tops were found in some plots. After a careful visual check using the nDSM and aerial photographs it was assumed that this is due to ground measurement errors
- Error - more than one automatically detected tree top point with-in the same reference tree crown having the height difference of more than 5m. A hypothesis could be established taking in to account that no such tree was measured in the field which could be a 2^{nd} or 3^{rd} tier plant though it was detectable automatically. But it was considered as an error because no field measured data was available to confirm the hypothesis. In some cases, more than one tree top was detected with in the tree crown nearly at the same height level. Such extra tree tops has been considered as error points

The clusters obtained were evaluated against the field inventory data. This validation was based on the spatial relationship between the field measured tree tops, the tree crowns and the automatically detected tree tops with reference to the above mentioned six classes. The distance was measured between the automatically detected tree tops and the field measured tree tops in the Euclidean 3-D space lying within, at the edge or outside the reference tree crown in ArcGIS environment. The ArcGIS shapefiles were generated for each sample plot for the visual inspection and evaluation. Each detected tree top was then assigned with appropriate class. Figure 2 shows an example of a sample plot with its related information.

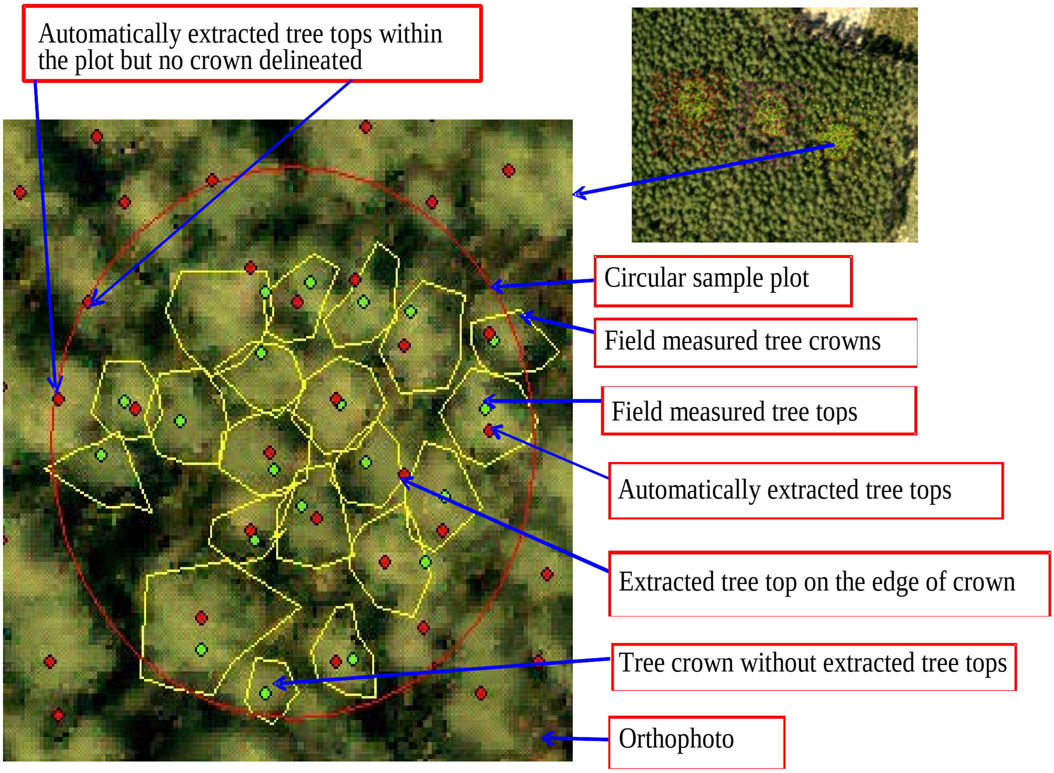


Figure 2. Field plot and related attributes with validation classes in a test area of Poland.

3. Results and Discussion

It was accepted that the whole single tree extraction in the natural forested condition is nearly impossible due to the high variation in the terrain, tree type, multistoried trees, tree density, tree crown density, crown width and gap variation. Therefore, each tree crown extracted has been considered as a single tree. After the pre-processing and the running of the modified *k*-means algfigorithm, the 3-D points of each tree cluster were extracted above 4m height. This was done to avoid the effect of low ground vegetation during the clustering process. From the 3-D points of an individual tree cluster, tree top points were extracted. The accuracy assessment of the four major validation classes of automatically detected tree tops with reference to the field measured tree tops has been presented in table 2.

According to the observations after the first validation, some tree tops (plots no. 5 of young Hornbeam and plots no. 21 of mature Scots pine) were wrongly detected at the outer edge of the respective reference tree crown on the same height level. But, such detected tree tops were present within different neighbouring crown, which put them in 'doubtful' category. Such 'doubtful' cases were considered as correctly detected tree tops after the visual checks. This was due to inaccurately delineated reference tree crown. In plot no. 5 (young Hornbeam) and plots dominated with young and mature Scots pine (6, 8, 9, 11, 12, 13, 14, 15, 16, 17, 18, 20, 21 and 25), some detected tree tops were outside the edge of the reference tree crowns at the same height level and therefore, were kept in 'nearly exact' class.

In plots dominated with young and mature Scots pine (6, 7, 8, 9, 13, 15, 17, 19, 22, 24 and 25) there were more automatically detected tree tops within each plot but there were no reference tree crowns and tree tops. Such trees have been classified as 'ignored' (see table 3) after the visual inspection using aerial photographs and nDSM images.

In plots 7 and 18, dominated with mature Scots pine, few reference tree tops were just outside the edge of the respective tree crown within the plot. Such tree tops were included as correct reference tree tops and were put under an appropriate class after validation. In some plots, dominated with the young Scots pine (11, 16 and 20) and the mature Scots pine (18 and 19), few extra tree tops were detected as 'error' points as they did not match with any tree crown or nearest reference tree top. In some plots, no reference crowns were present for the trees crowns that were intersecting more than 50% of the plot boundary, however, tree tops were detected after applying the algorithm (see figure 2). Such detected tree tops were also classified as 'error' due to lack of the reference tree top and reference tree crown. In few plots, positional shifts were up to one-third in some of the reference tree crowns, and between reference tree tops and detected tree tops. This was found while evaluating through aerial photographs and nDSM (see figure 2). In general, it was found that the automatically detected tree tops were better positioned than the field measured ones, while making a comparison through aerial photographs and nDSM. The higher accuracy could be attributed to more accurate GPS instrument used during the airborne LIDAR measurements.

After rearranging the result as displayed in table 2 by including 'ignored' and 'error' classes, the final result is shown in table 3.

In the case of the plots 6, 7, 8 and 25 (dominated with mature Scots pine), due to addition of 'ignored' points, the automatically detected tree tops got outnumbered (>100%) than the reference tree tops (see table 3) due to missing field measured tree tops. The result from table 3 show that 83.8% of the average accuracy was achieved in all 25 plots using the modified *k*-means algorithm with reference to the field inventory data.

A species-wise comparison was also made from the automatically detected tree tops during the validation procedure as shown in table 4.

There is a distinct difference in the tree top count of automatically detected trees and the reference trees of relatively young age with high tree density in the three tree species (European beech, Hornbeam and Scots Pine).

For younger species, the tree top count was lower than the mature ones of the same species due to the omission of very close seed points below the d_{thres}. For example, in the case of plot 1, dominated by relatively young European beech of an average age 87 years, a low number of tree tops were detected as compared to the plots 3 and 4 containing mainly older tree species of an average age of 142 and 152 years, respectively (see table 3). A similar result was found for plot no. 5 with young Hornbeam trees of an average age of 50 years (there is no any other Hornbeam plot to compare) and plots 10, 16 and 20 (young Scots pine), with trees of an average age of 57, 33 and 42 years, respectively. The average percentage accuracy of the detected tree tops of dominant tree species present in the study area has been shown in table 6.

From the table 2, the average percentage accuracy for the automatically detected 'exact' and 'exact' + 'nearly exact' tree tops has been calculated and the result has been presented in table 5.

From table 5 it is clear that in the case of matured European beech and Scots pine, the average percentage accuracies for 'exact' tree tops are ~70% and ~78%, respectively. While in the case of matured European beech and Scots pine, the 'exact' + 'nearly exact' tree tops together taken into consideration, the average accuracies are ~85% and ~84%, respectively. In the case of young European beech and Scots pine, the average percentage accuracies for 'exact' tree tops, are ~38% and ~54%, respectively. The average percentage accuracies in case of 'exact' + 'nearly exact' tree tops of young European beech and Scots pine increased to ~48% and ~59%, respectively. For a single plot of matured Oak species, the average accuracy for 'exact' and 'exact' + 'nearly exact' tree tops is almost the same (~64%) because 'nearly exact' tree tops were not extracted in this case. For a single young plot of Hornbeam, the average accuracies for the 'exact' and 'exact' + 'nearly exact' tree tops are ~40% and ~53%, respectively. In all relatively younger plots of different tree species, the result for 'exact' and 'exact' + 'nearly exact' tree tops were not satisfactory (see table 5).

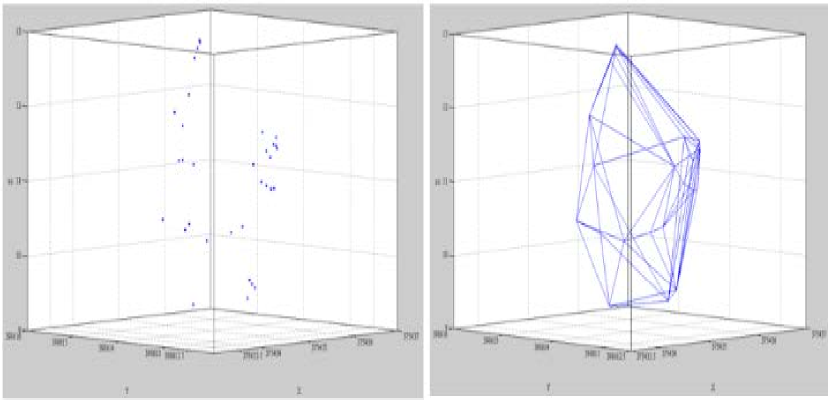
The overall average percentage accuracy substantially improved in all cases once the 'doubtful' tree tops from table 2, and 'ignored' and 'error' cases from table 3 have been considered in the validation procedure (table 3). The exceptions were plot no. 18 containing of mature Scots pine and plot no. 20 containing young Scots pine as shown in table 3. A species-wise average percentage accuracy of detected tree tops has been summarised in the table 6.

It is noticeable from table 6 that the modified *k*-means algorithm worked well for both deciduous and coniferous species. The performance of the algorithm using low density (7 points m^{-2}) first and last pulse normalized LIDAR data in leaf-on season can also be compared to the result reported in the literature using different approaches (Heurich 2006, Holmgren and Persson 2004, Packalén and Maltamo 2007, Reitberger *et al.* 2008c, Vehmas *et al.* 2008, Wang *et al.* 2008b). The result from table 6 shows that an average of nearly 86% of the matured deciduous and nearly 93% of the matured coniferous trees were extracted by the presented approach. Almost equal average accuracies were obtained in the case of young deciduous and coniferous tree species (58%). The above result also shows that for the plots containing mature trees, the algorithm worked relatively well as compare to the younger ones of the same tree species. Even with an incomplete assessment of all tree species, LIDAR data has became an efficient means to support small to large-scale inventories. This is because the reasonably correct and rapid assessment of information about dominant trees provides a valuable basis for the derivation of forest parameters needed for sustainable forest management. In addition, the correct delineation of single or scattered trees in the forest landscape is also of high value for a number of management tasks (Koch *et al.* 2006). The accuracy achieved using the presented vector based study was found better compared to the height based filtering method used by Pitkänen *et al.* (2004), where only about 40% of all trees were detected and a large number of suppressed, small trees were not detected from the unfiltered nDSM. In addition, the number of false detection was very high (~65%) in their unfiltered nDSM approach. They also concluded that more trees are detectable by tuning the variables but this again causes an increase in the percentage of false detection at the same or faster rate. This shows the need for parameter adjustment before the tree detection, which was implemented in the presented method.

In this study, the number of trees to be extracted is decided by the number of external seed points to be used during the initialisation of the *k*-means, which, in turn, is dependent on the σ and d_{thres}. This was in contrast to the study conducted by Ko *et al.* (2009) in which they derived the branches of deciduous and coniferous trees by calculating the mean silhouette values repeatedly for different *k* values. The method presented by Ko *et al.* (2009) for finding the suitable value of *k* for different tree species of different age groups in different forest condition for a larger area is not a feasible one. The local maxima method has also certain limitations in finding accurate seed points for crown delineation (Maltamo *et al.* 2004, Wulder *et al.* 2000, Tiede and Hoffmann 2006), especially in the dense and highly structured forest (Tiede *et al.* 2008). It was noted that the d_{thres} setting becomes more difficult with the increasing forest complexity. For example, the plot containing mainly older trees with higher crown width requires higher d_{thres} because local maxima from smaller peaks will most likely represent only branches, hence needs to be eliminated in the later step. Whereas, the local maxima from a peak in a plot containing younger coniferous trees will most likely to be a tree top, hence requires comparatively smaller d_{thres} to restore it. In addition, during the investigation it was found that the smoothing done on the nDSM, a step before extracting the local maxima, is not necessary if the threshold distance is appropriately set to filter out the unwanted local maxima. The smoothing on the nDSM removes the noise present in the image and blurs it. At the same time, it removes the details also. Setting the threshold (a measure for how much noise should be removed) and kernel size (radius of the area considered when changing pixels while convolution) are two important user-defined parameters while smoothing. Alternatively, with the use of d_{thres} directly in the pre-processing step, the smoothing can be avoided and the risk of losing the information from the nDSM is being reduced. On the other hand, the smoothing eliminates first all the weak maxima (with low grey value) which are produced mainly from the branches of the individual trees than the tops of the trees. This situation is of higher significance in the case of trees with wider canopies or complex forest structure with dense canopies and small canopy gaps. Therefore, the selection of local maxima is a user-dependent choice within the given method. The region growing algorithms use local maxima as seed points to delineate the tree crowns and work in the image domain. While, the presented modified *k*-means uses the local maxima as external seed points and work purely in vector domain using normalized LIDAR data. The external seed points used in the modified approach is to avoid the random selection of the machine generated user-defined seed points to partition the whole data set in to clusters. The possibility that the laser scanner might have missed the highest point of the tree, a problem sometime related to the specific shape and structure of the tree (crown height, crown width and crown density), cannot be ignored. Crowns, especially deciduous tree crowns, with more than one local maximum are due to its flat, rather than conical shape. It is difficult to identify only one local maximum per tree crown in case of understory trees, which are only partly visible. The multiple crowns further complicate the identification of only one local maximum per tree crown (Tiede *et al.* 2008). It was assumed that the filtering of nDSM image might move the locations of local maxima slightly compared to the original image in some cases. It was expected that more intense the filtering, more bias is the estimated height compared to the original height, hence low to moderate smoothing was applied.

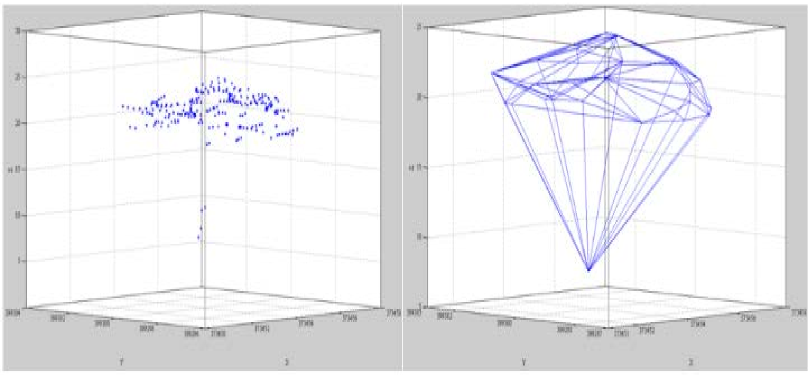
The LIDAR data is not randomly positioned on the 2-D surface. There are gaps in between the LIDAR point clouds. In case of the reflection from a tree, these could be canopy gaps. This is due to the LIDAR system, scan angle, point density and forest structures. The *k*-means algorithm depends both on the input data distribution and input parameters assigned during the run-time. For example, missing points (canopy gaps) in the input data could move the position of the centroid during the algorithm runtime slightly. There are possibilities that the centroid could shift from the middle of the tree cluster to the denser part of the local tree cluster resulting in skewed tree clusters. However, such case was not visible after random visual check of the sample tree clusters. The shape of the output individual tree cluster to be extracted is dependent on the constant height reduction factor applied on the external seed points and the normalized LIDAR data before the modified *k*-means initialisation. Once the clustering was over, the height value was scaled-up to its normal.

The reconstruction of the cluster is a valid option to depict its shape in the geometrical form. The shape characteristics of the tree crowns are dependent on many factors like age, the forest condition in which the tree crown grows (open, moderately dense and very dense) and the influence of human-induced factors. Two examples of the clusters containing points of young and matured individual tree and their respective 3-D convex polytopes have been represented in figures 3 and 4.



(a) (b)

Figure 3. Young Scots pine cluster (a) and the respective 3-D convex polytope (b).



(a) (b)

Figure 4. Matured Scots pine cluster (a) and the respective 3-D convex polytope (b).

The triangulation of the surface through forming the facets from vertices using QHull algorithm can be easily seen in figures 3 and 4. In both the cases, facets were successfully formed even when there was a gap in clusters containing LIDAR points obtained after running the algorithm. The shape of the 3-D convex polytope formed from the respective extracted cluster denotes the approximate shape of the individual tree as is present in the field. However, in the present study, due to lack of the field photograph of a particular tree, it was not possible to show the shape correlation.

4. Conclusion

The modified *k*-means algorithm based on first and last pulse ALS data for 25 test plots in the Polish forest area performed well for the single tree extraction above 4m height. LIDAR data were processed above 4m height in order to avoid the bad clustering due to low ground vegetation such as bushes and grasses. The traditional *k*-means method generates arbitrarily bad clustering due to randomisation of the process. The iterative partitioning based modified *k*-means algorithm is comparatively good for partitioning natural objects when user has a control over the seeding and the points are brought closer in z-dimension before the initialisation of the algorithm. A different σ value was used while smoothing the nDSM before extracting the seed points. The mean height value of the trees and the corresponding σ value range were 30-34m σ 1.3-1.4 for three European beech dominating plots; 31m σ 1.0 for a single Oak dominating plot; 22m σ 0.9 for a single Hornbeam dominating plot and 12-24m σ 0.6-0.8 for twenty Scots pine dominating plots. In general, the value of σ used for the deciduous tree dominating plots was higher compared to the coniferous plots.

The individual tree level reference data of each plot with species-specific information helped in validating the result at individual tree level as presented in tabulated forms. The results in section 3 shows that the modified *k*-means algorithm worked equally well both for mature deciduous and coniferous tree species. The result also shows that the algorithm for the mature and older tree species worked better as compared to the relatively younger ones irrespective of species. It was assumed that more studies are required to be done in different forest conditions in order to establish a better estimate.

The detection of small or suppressed trees is still a problem. In a dense deciduous forest with tightly interlocked, homogeneous canopy, it was difficult to separate tree crowns from each other by applying the algorithm. Thus, the tree number was underestimated. In the case of young tree species, which have a high tree density, sufficient number of external seed points could not be generated by the modified algorithm. This was mainly due to omission of very closely spaced seed points. The problem could not be solved even by changing the variables in the pre-processing steps. As a result, in such cases, relatively low number of tree tops were detected from the algorithm as compared to the field inventory data. It was found that scaling down the height value of the normalized 3-D LIDAR points as well as the seed points, helps in minimising the intra-cluster variance or the squared error function, which is the ultimate objective of the *k*-means method. The number of trees to be extracted is decided by the number of external seed points to be used during the initialisation of the *k*-means, which, in turn, is dependent on the smoothing factor and d_{thres}. The shape of the output individual tree cluster to be extracted is determined by scaling down the height value of the external seed points and the normalized LIDAR data before the cluster initialisation. The reduction of z-coordinates was kept constant for all the plots (half). It can be concluded that the empirically found distance threshold is one of the significant parameters in the extraction of the number of external seed points during the pre-processing steps and the performance of the algorithm. The investigation shows that the d_{thres} is a forest dependent variable and the setting procedure of this threshold is an important input in tree extraction. The value of d_{thres} for younger trees with single and narrow crown at the tree top or conifers was found between 2-3m with very gentle smoothing. While, the d_{thres} for the relatively older trees with wider crown diameter and more intermittent peaks at the top or broadleaved trees was varying between 2-5m with gentle to strong smoothing. It can be concluded that the d_{thres} setting becomes more difficult with increasing forest complexity. During the investigation, it was found that the smoothing is not mandatory if the threshold distance is appropriately set to filter out the unwanted local maxima. The smoothing on the nDSM distort the image quality and removes the details. On the other hand, smoothing eliminates first all the weak maxima being probably produced from the branches of the trees than the tree tops. Thus, the value of σ used during the smoothing and the d_{thres} used for the removal of extracted unwanted seed points are important user controlled forest dependent variables in this approach. This is important in the case of trees with wider crowns at the top or in mixed forest conditions. The dependency about the number of trees to be extracted cannot be replaced by merely applying simple *k*-means procedure that implies random selection of user-specific *k* seed points that often result in arbitrary number of clusters of poor quality (Gupta *et al.* 2010). Therefore, there is an obvious advantage of the modified *k*-means approach used in this study over the simple *k*-means or hierarchical based clustering (Gupta *et al.* 2010) or other approaches using *k*-means used for single tree extraction by other investigators such as Morsdorf *et al.* (2003) and more recently Ørka *et al.* (2009b). The number of trees to be extracted depends on the *k*-value but it is not the sole criteria to extract the tree in its appropriate form, and therefore cannot be validated as such. The result was validated by comparing the automatically detected tree tops with reference to the field measured tree tops as outlined in the section 2.6.

Testing the developed algorithm in 25 Polish test sites and comparing the results with the available field inventory data has a significant role in the algorithm establishment for single tree delineation. This was instrumental in improving the algorithm at the pre-processing and during the main processing steps in order to extract single trees with acceptable accuracy. The significance of a pre-knowledge about the test site can't be ruled out in setting the variables used during the investigation. In case of Poland test sites, the single mature dominant tree species (Scots pine) in 17 out of 25 plots has led to higher accuracy (see table 6) even when first and last pulse airborne LIDAR data of low point density (7 points m^{-2}) was used.

The main problem in validating the results is the availability of correct field inventory data in some cases. The validation of the field data after a careful visual check showed that the positioning of some of the reference data was erroneous, even after some corrections. The main error in coordinates could be attributed to the fact that different types of GPS instruments have been used and a different signal quality was received in the forest during the field and airborne measurements. In the field, the position of each tree top and trunk was measured with Sunnto instruments. The inaccuracy for the measurements with the Sunnto instrument might be higher than the measurements from the ALS according to the visual checks using the aerial photographs and nDSM images. This leads to inaccuracies during the validation procedure. The problem was reduced using 'ignored' tree tops class. However, by adopting this in four Scots pine plots (plot no. 6, 7, 8, and 25), an overshooting in the number of detected tree tops was found as compared to the field inventory tree tops (see table 3). On the other hand, from airborne measurement, it is hard to find the tree trunk position mainly due to obstruction by the tree crowns. During the field measurements, the distance from the middle point to a tree trunk was a criterion whether the tree should be included or excluded from the sample plot. If the distance (from the middle point to a tree trunk) to a tree and half of its diameter is added and the result is less than the sample plot radius, then the tree was included in the respective sample plot. Sometimes, the trees grow not straight but crooked. Because of this reason, some crowns were inside the sample plot while its trunk was outside. The tree tops extracted from such crowns have been included in the 'ignored' class.

The quality of the final solution largely depends on the forest characteristics in which the algorithm has to be applied, the LIDAR point density, the threshold distance and the initial set of clusters to be used during the algorithm run-time. The point density of the extracted cluster has a direct effect on the shape of 3-D convex polytope. If the reflected hits obtained in the original LIDAR data are from the tree trunk positions, then more appropriately obtained is the shape of the tree through 3-D triangulation mechanism. On the other hand, if the number of vertices in the cluster is too small, then the polytope formation fails. However, such incident was very rare.

In the future, the algorithm will be implemented for the single tree delineation with the point clouds derived from the full waveform ALS data of high point density (with or without utilising the other parameters like intensity and pulse width) in different forest conditions. A separate study also required to be done with the leaf-on and leaf-off datasets for better discrimination of tree species, particularly on the complex forest sites.

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1	2	3	4	5	6	7	8	9
Plot No.	Dominating Species	Avg. Age (Years)	Reference tree tops (Σ)	Exact (Σ)	Nearly Exact (Σ)	Gap (Σ)	Doubtful (Σ)	Auto. detected tree tops (Σ) (5+6+8)
1	Beech	87	21	8	2	9	2	12
2	Oak	142	14	9	0	4	1	10
3	Beech	142	7	4	2	1	0	6
4	Beech	152	6	5	0	0	1	6
5	Hornbeam	50	15	6	2	6	1	9
6	Scots pine	105	21	17	1	3	0	18
7	Scots pine	105	22	17	1	4	0	18
8	Scots pine	105	16	12	3	1	0	15
9	Scots pine	105	20	13	3	4	0	16
10	Scots pine	57	24	14	0	9	1	15
11	Scots pine	77	20	16	1	3	0	17
12	Scots pine	67	28	21	4	3	0	25
13	Scots pine	67	21	16	1	4	0	17
14	Scots pine	67	21	16	1	4	0	17
15	Scots pine	80	13	10	1	2	0	11
16	Scots pine	33	23	12	2	9	0	14
17	Scots pine	107	30	26	1	3	0	27
18	Scots pine	107	31	22	4	5	0	26
19	Scots pine	107	17	14	0	3	0	14
20	Scots pine	42	38	20	2	15	1	23
21	Scots pine	97	24	13	2	7	2	17
22	Scots pine	97	20	16	1	3	0	17
23	Scots pine	97	22	21	0	1	0	21
24	Scots pine	97	25	22	0	3	0	22
25	Scots pine	107	18	14	1	3	0	15
	Σ		517	364	35	109	9	408
	%		100.0	70.4	6.8	21.1	1.7	78.9

Table 2. Primary result after validation.

1	2	3	4	5	6	7	8	9

Plot No.	Dominating Species	Avg. Age (Years)	Sum of reference trees tops	Sum of auto. detected trees tops (Exact, Nearly Exact, Doubtful)	Ignored	Error	Final auto. detected tree tops (Σ) ((5+6)-7))	Final auto. detected tree tops (%)
1	Beech	87	21	12	0	0	12	57.1
2	Oak	142	14	10	0	0	10	71.4
3	Beech	142	7	6	1	0	7	100.0
4	Beech	152	6	6	0	0	6	100.0
5	Hornbeam	50	15	9	0	0	9	60.0
6	Scots pine	105	21	18	5	0	23	109.5
7	Scots pine	105	22	18	5	0	23	104.5
8	Scots pine	105	16	15	3	0	18	112.5
9	Scots pine	105	20	16	3	0	19	95.0
10	Scots pine	57	24	15	0	0	15	62.5
11	Scots pine	77	20	17	0	1	16	80.0
12	Scots pine	67	28	25	0	0	25	89.3
13	Scots pine	67	21	17	3	0	20	95.2
14	Scots pine	67	21	17	0	0	17	81.0
15	Scots pine	80	13	11	1	0	12	92.3
16	Scots pine	33	23	14	0	1	13	56.5
17	Scots pine	107	30	27	2	0	29	96.7
18	Scots pine	107	31	26	0	1	25	80.6
19	Scots pine	107	17	14	1	1	14	82.4
20	Scots pine	42	38	23	0	2	21	55.3
21	Scots pine	97	24	17	0	0	17	70.8
22	Scots pine	97	20	17	2	0	19	95.0
23	Scots pine	97	22	21	0	0	21	95.5
24	Scots pine	97	25	22	1	0	23	92.0
25	Scots pine	87	18	15	4	0	19	105.6
	Σ & %		517	408	31	6	433	(83.8%)

Table 3. Final result after validation.

Species ID	Dominating Species	No. of Plots	Total No. of reference crowns and tree tops	% of field detected tree tops in fraction for each tree species	Total Area (ha)	Total No. of auto. detected tree tops	% of auto. detected tree tops for each tree species
1	European Beech	3	34	6.6	0.19	25	73.5
2	Oak	1	14	2.7	0.05	10	71.4
3	Hornbeam	1	15	2.9	0.02	9	60.0
4	Scots pine	20	454	87.8	0.76	389	85.7
Σ & %		25	517	100.0	1.02	433	83.8

Table 4 species-wise accuracy assessment of the result

Species	Type	Stage	Average % accuracy (Exact)	Average % accuracy (Exact + Nearly Exact)
European Beech	Deciduous	Mature	70.2	84.5
European Beech	Deciduous	Young	38.1	47.6
Oak	Deciduous	Mature	64.3	64.3
Hornbeam	Deciduous	Young	40.0	53.3
Scots pine	Coniferous	Mature	77.5	84.3
Scots pine	Coniferous	Young	54.4	59.0

Table 5. Species-wise average accuracy (%) for the automatically detected 'exact' and 'exact' + 'nearly exact' tree tops.

Species	Stage	Average % accuracy
European Beech	Mature	100.0
European Beech	Young	57.1
Oak	Mature	71.4
Hornbeam	Young	60.0
Scots pine	Mature	92.8
Scots pine	Young	58.1

Table 6. Species-wise overall average accuracy (%) for the automatically detected tree tops.