In: Wagner W., Székely, B. (eds.): ISPRS TC VII Symposium – 100 Years ISPRS, Vienna, Austria, July 5–7, 2010, IAPRS, Vol. XXXVIII, Part 7B

TREE SPECIES DETECTION USING FULL WAVEFORM LIDAR DATA IN A COMPLEX FOREST

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Commission VII, TC VII Symposium

KEY WORDS: LIDAR, Extraction, Reconstruction, Algorithms, Pattern, Three-dimensional

ABSTRACT:

The three-dimensional single tree extraction by applying pattern recognition based modified clustering approach on full waveform normalized raw LIDAR data has been presented in this research work. The LIDAR data of medium density (16 points m^{-2}) was collected in August 2007 from the administrative forest district Hardt, Germany. The total study area is 1.75 ha and dominated by various deciduous tree species. The study plots selected contains multi-tier tree species of different age groups. Clusters of single tree extracted after running the algorithm were reconstructed using QHull algorithm. A validation procedure was devised and used for the accuracy assessment of the automatically detected tree species with respect to the forest inventoried data. The average producer's and user's accuracy for the total study area was around 56% and 41%, respectively. The results showed that the modified algorithm worked fairly well in the detection of evergreen conifers (79%) than the deciduous tree species (47%) beside the fact that conifers constitute roughly 18% of the total study area. The result showed that the algorithm for the upper tier trees species which are relatively mature and older worked better as compared to the tree species lying beneath the first-tier. The mixture of multi-storey tree species of varying age and height quintile with dense canopy cover was a limiting factor in the detection of single tree automatically in the presented work and shows the future scope of improvement in the algorithm applied.

1. INTRODUCTION

In a complex forest ecosystem, finding the distribution of different tree species of varying age and height quintile through traditional methods is a very thorny job. In the past one decade, the demand for high quality LIght Detection And Ranging (LIDAR) data with more information has tremendously increased for various applications. The increasing demand of individual tree related information, as a basis to improve forest management performance, is the concerned factor for developing various methodologies for single tree extraction and related parameter estimation from airborne laser scanner (ALS) data. Clustering provide a good way of partitioning the whole normalized ALS dataset of the test area into an individual clusters. Because of the high point density full waveform LIDAR data provide a good platform to implement the clustering mechanisms via partitioning the data into individual clusters, each representing single tree. There are different clustering mechanisms, but the most popular *k*-means was chosen which is an iterative hill-climbing method and is a staple of clustering methods (Gupta et al., 2010). These has motivated to test the full waveform ALS data for the extraction of pattern of single tree crowns of different tree species in the selected plots of Hardt administrative forest district of Germany using modified clustering based approach and has been presented in the current work.

2. EXISTING RELATED WORK

Several studies has been carried out in the past on the application of airborne LIDAR data for vegetation related information retrieval using different methods (Hyyppä and Inkinen, 1999; Hyyppä et al., 2006; Ko et al., 2009; Nilsson, 1996; Persson et al., 2002; Persson et al., 2006; Vauhkonen et al., 2009; Wang et al., 2008). Research work using clustering based approaches for 3-dimensional (3-D) single tree extraction using airborne LIDAR data has been carried out (Cici et al. 2008; Doo-Ahn et al. 2008; Gupta et al., 2010; Morsdorf et al. 2003; Morsdorf et al. 2004; Reitberger et al. 2008). Morsdorf et al. (2003) used first and last pulse data with an overall density of 30 points m^{-2} and the *k*-means method to extract single tree in the Swiss National Park. In contrast to the modified algorithm used in the presented work, instead of scaling-down the height values, they scaled-up it by a factor of 3. This has been done to accommodate the aspect ratio of pine tree crowns (ranged from 3 to 6). However, it was concluded on the basis of previous study (Gupta et al., 2010) that by scaling down the height value of the normalized raw LIDAR points and the external seed points (local maxima), squared error function is minimized which is the ultimate objective of the *k*-means method. The closer the points will be, more precise will be the cluster formation with regard to actual tree/tree crown and its shape. The algorithm used in the presented work differs from Morsdorf et al. (2003) in a way that unwanted local maxima points were deleted in the pre-processing step. Riaño et al. (2004) estimated a derivative of foliage biomass, crown bulk density, using lidar metrics with *k*-means clustering at both plot and individual tree scales. However, individual tree level analyses were not completely successful in their work. In a study conducted by Ko et al. (2009) for deciduous-coniferous classification using single leaf-on high density full waveform

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LIDAR data, branches of 27 coniferous and 38 deciduous trees were derived by calculating the mean silhouette values repeatedly for different *k* values using simple *k*-means approach for improved visualization. The method lacks the efficiency for finding the suitable value of *k* with respect to different tree types, tree age and forest conditions. In their study the result is not validated using any field data. Ørka et al. (2009) tested the supervised classification strategy using linear discriminant analysis (LDA), random forest (RF) algorithm and support vector machines (SVM) for tree species classification. They also used unsupervised *k*-means clustering and *k*-means clustering in combination with the unsupervised random forest algorithm for the same purpose. However, their result showed that accuracies were lower in case of unsupervised one than for supervised methods applied for overall species classification. This shows that supervised methods are more promising which was found true during the investigation after a comparative qualitative analysis of the output by applying different clustering algorithms (Gupta et al., 2010). Vauhkonen et al. (2009) used LDA for the classification of individual trees and alpha shape metrics for tree species classification in Scandinavian test site comprising 92 trees detected and delineated manually from a very dense ALS data. However, the method applied required to be tested for larger dataset with lower or medium point density by automatic detection. Apart from tree detection methods, a method for reconstructing the tree crowns was also provided (Pyysalo and Hyyppä, 2002). There are many ways for constructing the shape of extracted points of single tree using different computational geometry concept like convex hull, 3D Delaunay triangulation or can be shown as 3-D surface or mesh.

3. MATERIALS AND METHODOLOGY

3.1 Study Area

Investigations were carried out in the selected plots of administrative forest district Hardt, Baden-Württemberg region in the South-West of Germany. The study area is flat, 1.75 ha in total, comprising 7 rectangular study plots, each of size 0.25 ha.

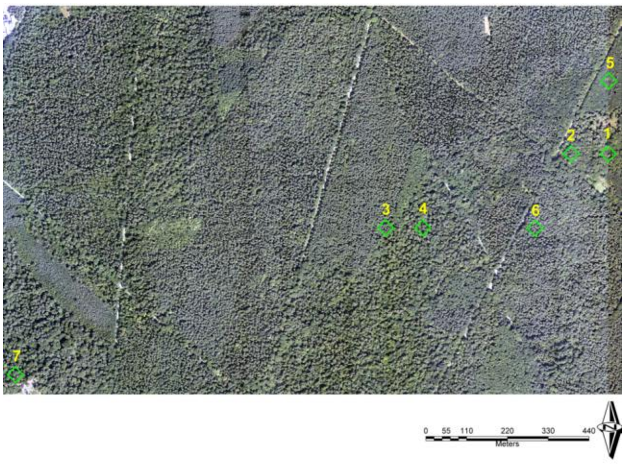

Figure 1. Location of rectangular study plots (green) as seen in the RGB aerial photograph

The study plots in the forest are characterized by a variety of deciduous and coniferous tree species of different ages. The forest is marked with highly interconnected and dense standing deciduous crowns. The overall fraction of deciduous and evergreen coniferous tree species is nearly 82% and 18%, respectively. Except plot 3, rest of the plots are dominated by deciduous trees species (Table 2). The dominant tree types in the studied field plots are Scots pine (*Pinus sylvestris* – 13.9%), Cherry (*Prunus avium* – 23.7%), Oak (*Quercus petraea* – 24.3%), European Beech (*Fagus sylvatica* – 21.1%), Hornbeam (*Carpinus betulus* - 9.5%) and 7.6% others species (Norway spruce - *Picea abies*, Douglas fir - *Pseudotsuga menziesii* and few other minor species). All the study plots are made up of multi-storey canopy layers. From the field inventory data collected, it was found that the height of different tree species of analyzed study plots varied between 8-35 m and average height ranged between 8-31 m.

Plot Id	Tree type	Tree species	% of tree
1	Deciduous	Hornbeam + Cherry	34.4 + 56.2 = 90.6
	Evergreen conifer	Scots pine	9.4
2	Deciduous	Cherry + Oak	91.8 + 4.1 = 95.9
	Evergreen conifer	Scots pine	4.1
3	Deciduous	Red Oak + European Beech + Black Locust	8.3 + 25.0 + 5.6 = 38.9
	Evergreen conifer	Scots pine + Douglas fir + Norway spruce	44.4 + 13.9 + 2.8 = 61.1
4	Deciduous	Hornbeam + European Beech	68.2 + 9.1 = 77.3
	Evergreen conifer	Scots pine	22.7
5	Deciduous	Oak + European Beech + Linden + Silver Birch	73.2 + 18.8 + 3.0 + 1.0 = 96.0
	Evergreen conifer	Scots pine	4.0
6	Deciduous	European Beech + Sycamore Maple	72.4 + 2.1 = 74.5
	Evergreen conifer	Scots pine	25.5
7	Deciduous	European Beech + Sycamore Maple + Cherry + Hornbeam + Oak	10.0 + 6.7 + 40.0 + 13.3 + 3.3 = 73.3
	Evergreen conifer	Scots pine + Norway spruce	6.7 + 20.0 = 26.7

Table 2. Tree species distribution

The name and distribution of tree species in Table 2 are in the same order.

3.2 Field Data Characteristics

Forest inventory data of the study plots was provided by the Forest Research Institute (FVA) of Baden-Württemberg. All trees in the plot above 7 cm diameter at breast height (DBH) were measured. Two top heights of the main tree and one top height of the dominated tree were measured using a Vertex® instrument. The arithmetic mean of the height measurements was calculated as an average top height for each plot (Straub et al., 2009). Stand height curves with the DBH as input variable were used to estimate the heights of the remaining trees (Korn-Allan et al., 2004). Several height percentiles were calculated for each inventory plot based on the nDSM and LIDAR points (Straub et al., 2009). Further, field work was conducted for plot establishment and measuring coordinates. Coordinates of center point and four corners of each rectangular plot were measured. Some other parameters like azimuth and distance from the middle point of each sample plot to sampling tree inside the plot were also taken. Tree coordinates were then derived using the azimuth and distance from the center point of each plot using compass and tape.

3.3 LIDAR Data and Pre-processing

Full waveform laser scanner data of density (16 points m^{-2}) was acquired during August 2007 by TopoSys GmbH using the Riegl LMS-Q56O system. Important flight and system parameters are given by Straub et al. (2009). Both the raster terrain and surface models of 50 cm resolution were calculated using the LIDAR raw point clouds. An 'Active Surface Algorithm' implemented in the "TreesVis" - software for LIDAR data visualization and analysis, was used for data filtering and surface interpolation (Weinacker et al., 2004). A normalized digital surface model (nDSM) was derived by subtracting the digital terrain model (DTM) from the digital surface model (DSM) using "TreesVis" software. Raw full waveform LIDAR points were normalized using the DTM to ensure the absolute height of the object and to eliminate the influence of the terrain. Thus, obtained normalized raw data was further used in the main process for clustering.

3.4 Orthophoto Characteristics

RGB/NIR Optical data were collected by TopoSys GmbH in July 2008. Important flight and technical parameters of the RGB/NIR line scanner are given by Straub et al. (2009). The individual flight strips were rectified and georeferenced with the aid of DSM, which was filtered from ALS data (6-7 points m^{-2}) acquired at the same time with the optical data. Orthophotos were computed by the data provider and were delivered at 25 cm spatial resolution.

3.5 Data Processing

3.5.1 Clustering by Modified *k*-means: The *k*-means treats each observation in the input data as an object having a location in the space. The objective of *k*-means algorithm is to minimize the total intra-cluster variance or the squared error function. In the algorithm, the sum of absolute differences between each point and its closest centre in Euclidian 3-D space is minimized. Each centroid is the mean of the points in that cluster. 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 (Gupta et al., 2010).

The *k*-means algorithm was supervised to use the local maxima as external seed points to initialize the iteration, instead of selecting it randomly by the user, as in the case of Ko et al. (2009). This was done because finding the pattern of individual tree in natural forest conditions is very difficult by selecting *k* clusters randomly using the simple *k*-means algorithm. Another advantage of avoiding trial and error based simple *k*-means approach is saving of machine memory and total run-time. The performance of the algorithm was improved by reducing the height value of the data points and external seed points by a half. The reason behind the reduction of height value is that it brings the normalized raw points as well as seed points closer in z-dimension and minimizes the intra-cluster variance. Thus, it fulfils the sole objective of the *k*-means. The reduction of the height to half was found empirically with trial and error based approach and have been kept constant for all the 7 plots studied.

3.5.1.1 Extraction of external seed points and filtration of unwanted seed points: Local maxima points were extracted as external seed points above 5 m height from the nDSM image having a gray value larger than the gray value of all its 8 neighbors. To avoid the overflow of seed points, the points that were too close to each other were filtered out based on threshold distance. The filtered local maxima as external seed points in the *k*-means algorithm were finally used. The threshold distance, varied depending on the forest conditions. The plot dominated by mature or old trees requires higher thresholds distance because local maxima from smaller peaks will most likely represent only branches, hence needs to be eliminated. Local maxima from a younger tree's peak will most likely to be a treetop, hence, need smaller threshold distance. The value of threshold distance for younger trees with single and narrow crown at the tree top was found as approximately 2-4 m (plots 2, 5 and 6) without any smoothing. While threshold distance for trees with relatively older ones having wider crown with more intermittent peaks at the tree top was found as 4-6 m (plots 1, 3, 4 and 7) with no smoothing. However, this also varies from dominant tree types.

3.5.1.2 Modified *k*-means algorithm: The modified *k*-means algorithm applied to a set of 3-D vectors in the form of pseudo-code is given as follows.

(i) Select normalized 3-D LIDAR points and external seed points above certain height (for example, above 5 m)
(ii) For all the external seed points and that of the normalized LIDAR points, z = z*0.5, before initialization of the algorithm
(iii) Set $i = 1$
(iv) 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)
(v) 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)
(vi) $i = i$++ and update the means (C_j) to get a new set $C_1(i)$, C_2 (i), ..,$C_k(i)$
(vii) Repeat steps (iii) to (v) until $C_k(i) = C_k(i + 1)$ for all k
(viii) For all the external seed points and that of the normalized LIDAR points, z = z/0.5

3.5.2 3-D Reconstruction of tree clusters: Once the tree clusters are generated, each cluster is reconstructed in 3-D space 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 3-D tree crown cluster is constructed with triangular surface as a 3-D convex polytope. The convex hull of a set of points is the smallest convex set containing those points. For detailed introduction with example codes, see the book by O'Rourke (1994). 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. Thus, 3-D convex polytope each tree crown is shown as a 3-D object with a triangular surface in the case of 3-D convex polytope. The shape of each polytope is the representation of the respective tree species.

3.6 Validation Method

The automatically extracted tree tops of individual tree in each plot were validated with respect to field measured reference tree tops. A circular buffer of radius 3 m was created around each reference point, in Geographical Information System (GIS) environment. Only those extracted tree tops were considered which were close to a maximum of 5 m in 3-D Euclidean distance (ED) with that of the reference point. The extracted tree tops were intersected with that of the reference points of the identical plot within the buffered area. 3-D ED was calculated for each intersected point. Most suitable validation class as defined below was assigned for each intersected point.

3.7 Validation Classes

Following five validation classes were adopted for classifying the result and accuracy assessment.

(i) Exact (E) - only one extracted tree top with respect to the nearby reference tree top. 3-D ED between the extracted tree top and reference tree top point is ≤ 3 m.
(ii) Nearly Exact (NE) - one extracted tree top with respect to a reference tree top nearly at the same height level. 3-D ED between the extracted tree top and reference tree top is 3-5 m.
(iii) Split - more than one neighboured detected treetops up to the 3-D ED of 5 m from a neighbouring reference tree top.
(iv) Missing – includes those reference tree top points for which there is no extracted tree top point in the neighbourhood up to the 3-D ED of 5 m. It also includes the reference points for which there is no detected tree tops within the buffer around each reference tree top point.
(v) Extra - includes those extracted tree top points within the field boundary for which there is no reference tree top point up to the 3-D ED of 5 m. It also includes those extracted points within the field boundary for which there is no reference point within the buffer around each reference tree top point.

4. RESULTS AND DISCUSSION

Before running the modified *k*-means algorithm, normalized raw LIDAR points and local maxima points below 5 m height were filtered. This was done to avoid the effect of low ground vegetation and other smaller objects during the clustering process. After running the algorithm over normalized LIDAR points using local maxima as external seed points, the 3-D cluster points of the corresponding tree were extracted in all the study plots. Accuracy assessment of the five major validation classes of automatically detected tree tops with reference to the field measured tree tops has been presented (Table 3 and 4). Two validation classes, namely, (‘Exact’ and ‘Nearly Exact’) played a key role in determining the two kind of accuracy.

Plot ID	E	NE	S	M	Ex	$\sum_{EP}$	$\sum_{ErP}$	FD (%)
1	17	4	8	11	15	50	29	58
2	15	10	6	24	24	70	45	64.3
3	17	5	3	14	8	44	22	50
4	11	3	2	8	9	30	16	53.3
5	10	30	7	61	6	97	57	58.8
6	13	21	9	13	12	67	33	49.3
7	2	9	3	19	21	48	37	77.1

Table 3. Distribution of validation classes and other attributes

E = ‘Exact’ points, NE = ‘Nearly Exact’ points, S = ‘Split’ points, M = ‘Missing’ points, Ex = ‘Extra’ points, $\sum_{EP}$ = sum of extracted tree top points in the plot, $\sum_{ErP}$ = sum of extracted error tree top points in the plot, FD = False detected points = $\sum_{ErP}$*100/$\sum_{EP}$.

Plot ID	E+NE	$\sum_{EP}$	RP	P_acy (%)	U_acy (%)
1	21	50	32	65.6	42.0
2	25	70	49	51.0	35.7
3	22	44	36	61.1	50.0
4	14	30	22	63.6	46.7
5	40	97	101	39.6	41.2
6	34	67	47	72.3	50.7
7	11	48	30	36.7	22.9

Table 4. Plot level accuracy

E+NE = sum of exact and nearly exact points in the plot, $\sum_{EP}$ = sum of extracted tree top points in the plot, RP = total reference tree top points in the plot, P_acy (%) = producer’s accuracy = (E+NE)*100/RP and U_acy (%) = user’s accuracy = (E+NE)*100/$\sum_{EP}$.

It is visible from Table 4 that the producer’s and user’s accuracies in the broad-leaved deciduous dominated study plots (all plots except 3) are roughly varying between 37-72% and 23-51%, respectively. In case of plot 3, which is dominated by evergreen coniferous trees, the producer’s and user’s accuracies are approximately 61% and 50%, respectively. There are highest accuracies obtained in plot 6. The high producer’s and user’s accuracies in case of plot 6 are detected due to fewer tree species which are present nearly the same height level. Due to this factor closely-matched seed points were generated that resulted in a comparatively more accurately positioned detected tree tops with respect to the referenced tree tops. The false detection is lowest (49%) in plot 6 and highest in plot 7 (Table 3). In case of plots 2 and 7, the false detection is 64% and 77%, respectively, which is relatively higher than the remaining plots. It is noticeable that in both the plots, there are higher proportions of cherry trees. It is assumed that it was found difficult in automatic detection of small crowned and low height cherry trees. The accuracies are comparatively lower in case of study plots 5 and 7. In the former case (plot 5), it is mainly due to the mixed distribution multi-layered Oak and European beech with dense canopy. In the later case (plot 7), it is due to the presence of highly mixed tree species composition of varying age and high canopy density. In case of Oak dominated plot 5, the accuracies are not only lower but more or less in the same range. The average producer’s and user’s accuracies among all the study plots are 55.7% and 41.3%, respectively.

Table 8 shows the percentage distribution of ‘Exact’ and ‘Nearly Exact’ tree tops together and the corresponding reference tree tops for each species in all the 7 study plots.

Tree species	R_Tree %	E_Tree (E+NE) %
Scots pine	13.9	86.4
Norway spruce	2.2	42.9
Douglas fir	1.6	60.0
Hornbeam	9.5	66.7
Cherry	23.7	40.0
Oak	24.3	45.5
Red Oak	0.9	33.3
European Beech	21.1	47.8
Black Locust	0.6	100.0
Linden	0.9	33.3
Silver Birch	0.3	100.0
Sycamore Maple	0.9	33.3

Table 5. % distribution of 'Exact' (E) +'Nearly Exact' (NE) tree tops together and corresponding reference tree tops (R_Tree).

The species-wise distribution of the two accuracy determining validation classes (E+NE) gives a meaningful insight while assessing the accuracy. It is evident from Table 5 that the higher fractions of acceptable tree tops were detected for the evergreen Scots pine (86.4%). The detection of 'Exact' and 'Nearly Exact' tree tops is for few minor deciduous species like Black locust and Silver birch is highest (100%), while that of the other minor deciduous species like Red oak, Linden and Sycamore maple are 33.3% each. Average detection of 'Exact' and 'Nearly Exact' tree tops were found for the two other minor evergreen species, Norway spruce (42.9%) and Douglas fir (60%). Acceptable tree tops (E+NE) for Oak, Cherry, European beech and Hornbeam, which are the four major deciduous tree species in the study plots, are 45.5%, 40%, 47.8% and 66.7%, respectively. An overall 57.4% of trees were automatically detected together in the 'Exact' and 'Nearly Exact' validation class among the 7 test plots by applying the modified *k*-means algorithm. It is clear from the Table 5 that modified algorithm yielded higher amount of 'Exact' (E) and 'Nearly Exact' (NE) tree tops for evergreen coniferous trees despite the fact that it constitutes only 17.7% of total tree cover among all the 7 study plots. The percentage fraction of the sum of the tree top points in 'Exact' and 'Nearly Exact' validation classes among all the 7 test plots for the evergreen coniferous and deciduous trees are 78.6% and 47.1%, respectively. More than 80% Scots pines were detected in all the study plots by applying the algorithm. This may be due to their dominance in the upper canopy layer.

By applying supervised *k*-means approach, the number of trees to be extracted was decided by the number of external seed points used during the initialization of the *k*-means, which, in turn, is dependent on the distance threshold. During the investigation, it was found that the distance threshold is a forest dependent parameter. For example, the plot dominating with trees of wider canopies requires higher distance threshold because local maxima from smaller peaks will most likely represent only branches, hence needs to be eliminated. Whereas, local maxima from a peak in a plot containing trees with small canopies will most likely to be a treetop, hence requires comparatively smaller distance threshold.

Approximate shape of the individual tree crown was represented in the form of 3-D convex polytope. The convex polytopes were computed from the delineated clusters using QHull approach (Barber et al., 1996). Two examples of European beech and Scots pine from plot 6 containing clusters and the respective 3-D convex polytopes have been represented below in Figure 6 and 7, respectively. The European beech and Scots pine in the given examples are roughly 17 m and 26 m in height. The canopy cover and density played a vital role in computing the geometrical shape of the two tree species.

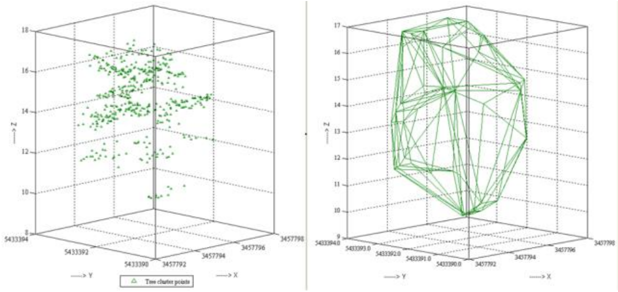

Figure 6. Cluster and convex polytope of a European beech

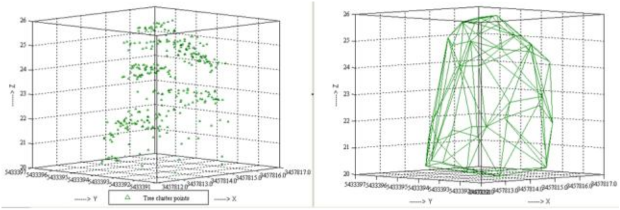

Figure 7. Cluster and convex polytope of a Scots pine

5. CONCLUSIONS

Traditional *k*-means generates arbitrarily bad grouping of objects due to random seed selection procedure and repeated run of the algorithm after cluster analysis to meet the fitness criteria. The algorithm yields comparatively fair results by partitioning the LIDAR data after seeding is done externally and the height value of the LIDAR points are scaled down to half before initialization of the process (Gupta et al., 2010). There is an obvious advantage of the modified approach over the simple *k*-means or hierarchical based clustering (Gupta et al., 2010) or other approaches using *k*-means for single tree extraction by other investigators (Morsdorf et al., 2003; Ørka et al., 2009).The formulation of validation method and classes were crucial in determining the accuracy.

The multi-tier, mixed tree species distribution with varying age groups, low crown diameter and dense canopy closure were big challenge for the algorithmic performance in single tree extraction for different tree species. The average producer's and user's accuracies among all the plots are 55.7% and 41.3%, respectively. From Table 4 it is evident that the performance of the algorithm is average in such forest conditions. It was observed that higher accuracies are tending to occur if the trees in plot are at nearly same height and when there are fewer tree species, as in the case of plot 6. The results show that the algorithm for the upper tier trees worked better as compared to the trees lying beneath it. Further algorithmic improvement and more investigation in varying forest conditions will be done to obtain better accuracies in the future.

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ACKNOWLEDGEMENTS

Landesgraduiertenförderungsgesetz (LGFG) Commission, Baden-Württemberg, Germany is acknowledged by the author for providing financial support during the research work within the framework of doctoral scholarship program. The authors would like to thank the Forest Research Institute of Baden-Württemberg (FVA) for providing the reference data for the study area. The authors also acknowledges his gratitude to his fellow colleagues Christoph and Johannes who have further conducted the field work for plot establishment in the test sites to get more forest parameters.