

# CLUSTERING IN AIRBORNE LASER SCANNING RAW DATA FOR SEGMENTATION OF SINGLE TREES

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## ABSTRACT

In recent years airborne laser scanning has been proven to be a helpful tool for remote sensing forestry applications. As laser scanning systems now provide very high point density ( $> 10 \text{ points}/\text{m}^2$ ), we pursue the approach of deriving geometric parameters on a single-tree basis. We explore the potential of delineating single trees from laser scanner raw data (x,y,z- triples) through cluster analysis and validate this approach with a dataset of about 2000 georeferenced trees. The dataset includes tree height and crown diameter and was gathered on a long term forest monitoring site by the Swiss Federal Institute for Forest, Snow and Landscape Research (WSL). A robust linear regression of field data tree heights with LIDAR derived tree heights leads to a slope of 0.91 and an offset of 0.71 m, with a RMS of 0.6 m. The accuracy of the laser scanner is evaluated through 6 reference targets, being  $3 \times 3 \text{ m}^2$  in size and horizontally plain. Internal offsets were found to be less than 0.25 m, the standard deviation of the points on the targets was about 0.06 m.

## 1 INTRODUCTION

The potential of airborne laser scanning for mapping forest stands has been intensively evaluated in the past few years, and algorithms deriving structural forest parameters (such as tree height, crown diameter, crown base height) in a spatial context have been successfully implemented by a number of researchers (Means et al., 2000), (Drake et al., 2002), (Naesset and Oekland, 2002). As LIDAR systems with high point density ( $> 10 \text{ points}/\text{m}^2$ ) are now available (Baltsavias, 1999), the derivation of these geometric properties on a single tree basis has been subject to recent research. Previous approaches mostly focused on segmentation of the Digital Surface Model (DSM) for the detection of single trees as for instance (Hyypäe et al., 2001) or (Persson et al., 2002). Since the processing step from the LIDAR point cloud to a DSM always includes loss of information, working on the LIDAR raw data has been increasing (Pyysalo and Hyypäe, 2002), (Brandtberg et al., 2003). (Andersen et al., 2002) have proposed fitting ellipsoid crown models in a Bayesian framework to the raw LIDAR data, including a probabilistic modeling of the crown - laser pulse interaction. We will present a practical two stage procedure for segmenting single trees from the LIDAR raw data itself. This leads to the ability of deriving geometric properties from segmented clusters of laser points belonging to a specific tree, without altering the original data.

## 2 DATA AND TEST SITE

### 2.1 Test site and Field Data

The test site is located in the Swiss National Park (SNP), being in an alpine region, and covers a height range from about 1800 m to 2400 m MSL. The dominant vegetation type are mountain pine (*pinus montana* ssp. *arborea*) and

larch, mixed with some alpine meadows. On a small subset of the test region, the Swiss Federal Institute for Forest, Snow and Landscape Research (WSL) maintains a long-term forest monitoring site. This site contains about 2000 trees with breast-height diameter (BHD) larger than 0.15 m, which have been geolocated and whose geometric properties including tree height, crown diameter and stem diameter have been measured using standard forestry tools. In Figure 1 an overview of the test site is given.

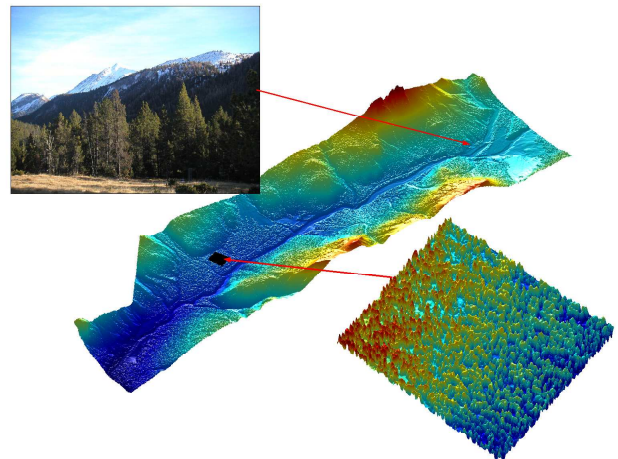


Figure 1: The Digital Surface Model (DSM) of the Ofenpass Area in the Swiss National Park. The area containing the long-term monitoring site of the WSL is enlarged. The photograph was taken on the day of the LIDAR flight.

### 2.2 Laser Scanning Data

In October 2002 a helicopter based LIDAR flight was carried out over the test area, covering a total area of about  $14 \text{ km}^2$ . The LIDAR system used was the Falcon II Sensor developed and maintained by the German company TopoSys. The system is a push-broom laser altimeter recording both first and last reflection from the laser signal on the

ground (first/last pulse). The flight was conducted with nominal height over ground of 850 m, leading to an average point density of more than 10 points per square meter ( $p/m^2$ ). A smaller subset of the area ( $0.5 km^2$ ) was over flown with a height of 500 m above ground, resulting in a point density of more than  $20 p/m^2$ , thus combining the two datasets yields to a point density of more than  $30 p/m^2$  for each of first and last pulse. The footprint sizes were about 30 cm in diameter for 850 m flight altitude and about 20 cm in diameter for 500 m altitude.

The raw data delivered by the sensor ( $x,y,z$  - triples) was processed into gridded elevation models by TopoSys using the company's own processing software. The Digital Surface Model (**DSM**, containing vegetation and/or buildings) was processed using the first pulse reflections, the Digital Terrain Model (**DTM**) was constructed using the last returns and filtering algorithms. The grid spacing was 1 m for the large area and 0.5 m for the smaller one, with a height resolution of 0.1 m in both cases.

### 2.3 Quality Assessment

The quality of the LIDAR data was assessed using 6 geometric reference targets being 3 by 3 meter in size. The targets were leveled to less than 0.5 degrees, using a digital angle meter. One of those targets is depicted in Figure 2. The positions of the 4 corners of each target were determined using a GPS and theodolite measurements, resulting in an internal accuracy of less than 2 cm. Regarding the models (**DSM/DTM**), the absolute positional accuracy was determined by Toposys (using the target positions) to be similar to or less than the resolution of the models, with horizontal positional accuracy being below 0.5 m and vertical accuracy less than 0.15 m. It should be noted that using this method only the accuracy of the LIDAR models in open areas is assessed, we can not make any statement about the accuracy in densely vegetated areas, where the **DTM** might have to be interpolated due to missing ground returns.



Figure 2: View of the Ofenpass area with two (one in the upper corner of the background meadow) geometric reference targets. The top of the targets was constructed using cardboard.

Furthermore, we used the reference targets to infer the noise of the sensor on a plain, homogeneously reflecting surface, which can be seen as a best case scenario. In order to get an estimate on the sensors noise, we calculated the standard deviation of all points reflected from the target, as

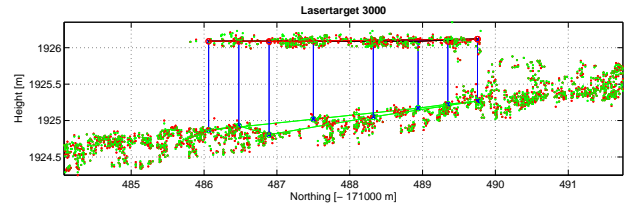


Figure 3: Side view of one of the 6 geometric reference targets with the LIDAR raw data points superimposed. Green points represent first pulse reflections, red points last pulse reflections.

ID	Points	$\Delta height$	$\sigma height$	$\Delta x$	$\Delta y$
1000	215	3	6.8	9	7
2000	266	-2	5.9	24	-11
3000	151	-2	6.6	6	6
4000	381	1	5.6	15	-3
5000	302	-2	5.8	4	15
6000	276	2	5.2	25	-18

Table 1: Using the reference target data, we calculated the mean height difference of all points ( $\Delta height$ ) on the laser target with the mean target height, the standard deviation of the points on the laser target ( $\sigma height$ ), and the differences of the positions of the centers of gravity ( $\Delta x$  and  $\Delta y$ ). The second column gives the number of points on a reference target, with first and last pulse being counted. The values in the last four columns are given in centimeter.

can be seen in Figure 3. A positional offset was calculated using the center of gravity (COG) derived from the laser points being on the targets with the COG of the targets themselves. These offsets only account for the internal accuracy of the adjusted laser-strips, since a previously found translational offset of 3.5 m in easting and 1 m in northing had been applied by Toposys to all of the data. The values for offsets and noise are listed in Table 1.

### 3 SEGMENTATION THROUGH K-MEANS CLUSTERING

Cluster analysis is a well known statistical tool for dividing feature spaces into areas containing values similar to each other, with this similarity being determined by a specific metric. In our case, the feature space is spanned by the coordinate axes  $x,y$  and  $z$  and we use a simple Euclidean distance metric. The  $k$ -means clustering algorithm itself tries to minimize the overall sum of distances of the points in feature space to their so-called cluster centroids or buoys. This happens in an iterative manner, where as a first step the initial centroids are most often randomly chosen, with the convergence of the clustering to a global minimum being heavily dependent on these starting locations. So the success of using cluster analysis boils down to a clever or exhaustive determination of these starting positions. Since pine tree crowns are of a general ellipsoidal shape, with the treetops being horizontally centered, we propose the use of local maxima derived from the **DSM** as starting positions (*seed points*). So the first stage of the segmentation process

will be the seed point extraction from the **DSM**, the second the cluster analysis starting off these locations.

### 3.1 Determination of Seed Points

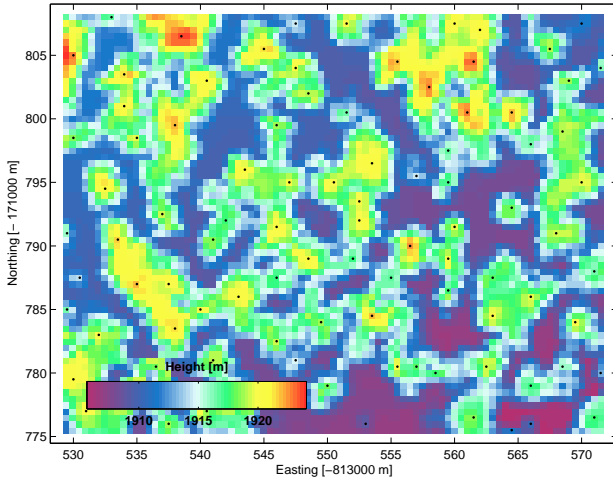


Figure 4: The seed points for clustering as automatically determined by local maxima filter used on **DSM**.

The extraction of local maxima from a depth image is generally not an easy task, with computational exhaustive watershed algorithms giving the best results for heterogeneous maxima shapes and sizes. However, as the size and/or shape of the trees is quite similar from one to the other, we use the approach of (Hyypäe et al., 2001). They proposed applying a smoothing filter on the **DSM** in order to smooth out the tree caps, followed by a morphological operation in order to find pixels having all 8 neighbors smaller than the center pixel. The kernel size and weights of the smoothing filter are important parameters, since they have to be tuned for each **DSM** resolution and expected crown diameters. Working with a grid resolution of 0.5 m and mean crown diameters of 1.7 m, we decided to use a 3x3 sized kernel with the following weights for a simple convolution,

$$\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} * \frac{1}{16} \quad (1)$$

which is the same kernel as in (Hyypäe et al., 2001). The outcome of this processing step is shown in Figure 4, with the black dots representing chosen local maxima. It should be noted that some humanly visible maxima have been missed, as well as there are probably too few local maxima in larger groups of trees. This causes problems with the segmentation, which will be discussed in Section 4.1.

### 3.2 Clustering in the Three Dimensional Point Cloud

Since clustering with an Euclidean metric favors ball shaped clusters in a three dimensional feature space, we introduce a scaling argument for the  $z$ -coordinate. This is done in order to accommodate for the aspect ratio of pine tree crowns, which in our case ranges from 3 to 6, hence the

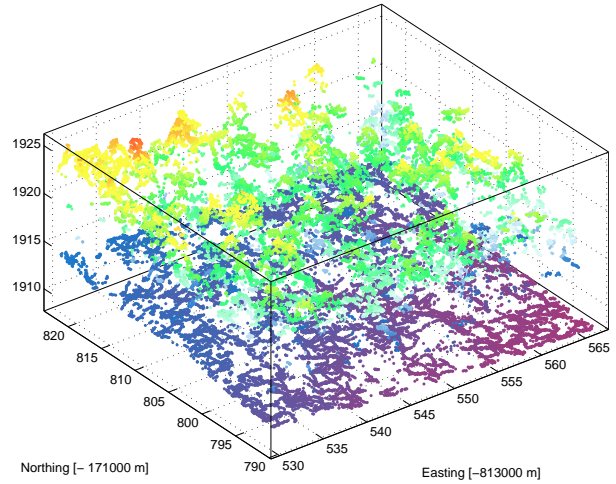


Figure 5: The LIDAR raw data ( $x,y,z$  - triples) as seen from the side, combined from the two over flights. Yellow and red represent high  $z$ -values, while blue and violet colors are low values.

height of the tree is 3 to 6 times larger than the crown diameter. Based on the field data, we have chosen a value of 3 as a starting point and have found good results using this scaling number for the  $z$ -axis. For clustering, both first and last pulse data is being used without differentiation of the two. The  $k$ -means clustering algorithm used is the one implemented in the Statistics Toolbox in MATLAB, using the information from (Spath, 1985). The algorithm clusters the data in an iterative process divided into two steps. The first step uses so called *batch updates*, where each iteration consists of reassigning points to their nearest cluster centroid all at once, which is followed by a recalculation of the cluster centroids. During the second step of *online updates* points are individually reassigned if that reduces the sum of distances and the cluster centroids are recomputed after each assignment. In order not to cluster ground returns as well, a cutoff distance of 1 m above ground was applied derived from the **DTM**. A sample of the raw data used is depicted in Figure 5. We combine the data from the two over flights, resulting in an extremely high point density ( $> 30 p/m^2$ ), however the segmentation works as well with a normal point density of about  $10 p/m^2$ , as can be seen in Figure 10, where only the data from the higher over flight has been used. It should be noted that the pine tree crowns in the test area are rather small in diameter (1.5 to 3 m), so that the high point density would compare to a normal point density in areas with larger tree crowns. As small-footprint LIDAR raw data can sum up to about 400 MB per  $km^2$ , this results in a large amount of time consuming processing, but since none of the steps described in this processing scheme does need human interaction, the processing can be done automatically. As clustering a larger area all at once is not feasible, we used 50 x 50 m windows with an overlap of 50 percent. The clustered data was joined automatically afterwards, eliminating double clusters and partial clusters at the edges. For the smaller subset of about  $0.6 km^2$  the clustering took about two days on a state-of-the-art PC, with still some redundancy due to the 50 percent overlapping clustering window, resulting in



clustering the whole area twice.

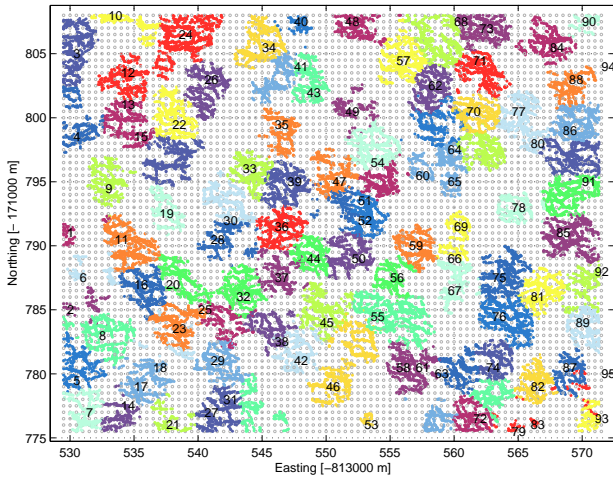


Figure 6: The segmented lidar points projected in the  $x,y$ -plane, the different colors represent the cluster assignment.

The outcome of the clustering is depicted in Figure 6. The raw data points have been projected in the  $x,y$ -plane for better visibility of the horizontal boundaries. The numbers represent cluster identifiers assigned during the segmentation process.

## 4 RESULTS

### 4.1 Matching the Field Data with the Tree Clusters

Since we had to deal with about 2000 trees residing in the database of WSL, we had to come up with some automatic matching of field tree data with cluster data. The total number of segmented clusters was considerably less than the number of field inventory trees (about 1200 compared to 1984), which is very likely due to the fact that in the field inventory, groups of trees standing very close to each other are identified as several single trees, whereas the LIDAR derived tree clusters are composed of all of these trees.

Having several stems very close to each other is a typical feature of the pine vegetation in the Swiss National Park. We solved this problem by assigning each field tree with the closest cluster, using both distance and tree height as matching criteria. This way, a cluster could be assigned to more than one field measurement, compensating for areas with several trees in a very small radius (typically less than 1 m). The outcome of this matching can be seen in Figure 7. Since the shown area is fully covered by field measurements, hence every tree with BHD larger than 0.12 m has been measured, using this approach of solving the tree merging problem is feasible in our case. Furthermore it is visible from Figure 7 that the matching is quite good for the middle and top-left region, while being considerably less good for the top-right and bottom-left region of the image. At these locations the WSL intensified their field work and added understory trees into their monitoring scheme. Hence we do have more field data trees being assigned to

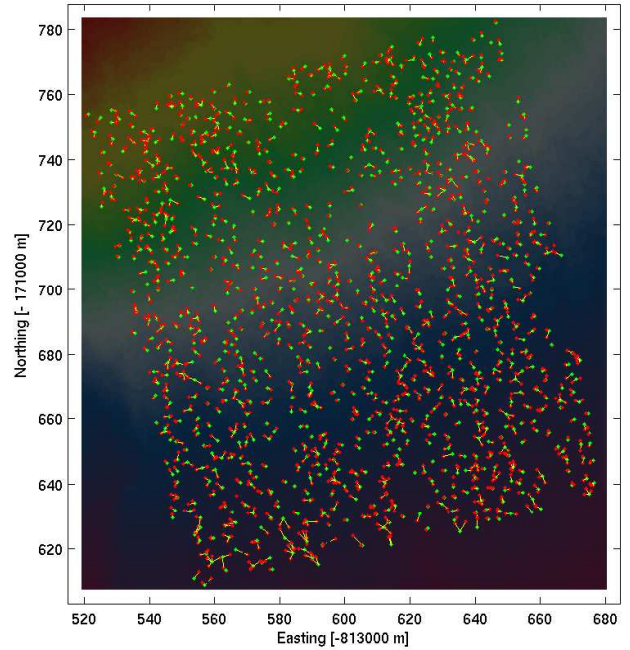


Figure 7: The matching of the field measured tree positions (red dots) and the LIDAR determined (green dots) positions is done automatically. The yellow line connects the matched tree locations. A LIDAR tree can be matched with more than one field data tree, in order to overcome the effect of "tree clusters", with a dominant overstory tree being surrounded by smaller, younger trees. The background image shows a color-coded and shaded representation of the DTM.

one LIDAR derived tree height in these regions. If more than one field measurement was assigned to a cluster, only the tallest tree was chosen for the robust regression below, since the highest point in the cluster would very probably be that tree.

### 4.2 Tree Height and Locational Differences

Having matched the clustered data with the field data, we can carry out a robust regression of LIDAR derived tree heights and field data tree heights. The tree height is derived as the maximum height of the LIDAR points belonging to a specific cluster. We chose to use a robust regression (Huber, 1981) over a normal linear regression, because of outliers introduced through the automated matching process, very probably because of mismatching. This can be done since far the most of the data points reveal the linear relationship (as inferred from the histogram of the weights used on the data values), and furthermore we have more than 900 data points allowing such a statistical approach. This robust regression calculates iteratively bisquare weights on those data points that do not fit the linear model in order to reduce their influence on the fit. The calculated errors for the linear model's coefficients are included in the graph. The linear fit reveals a slope less than 1 (0.91) and an offset of 0.71; this manifests a systematic underestimation of tree heights by the LIDAR data, which

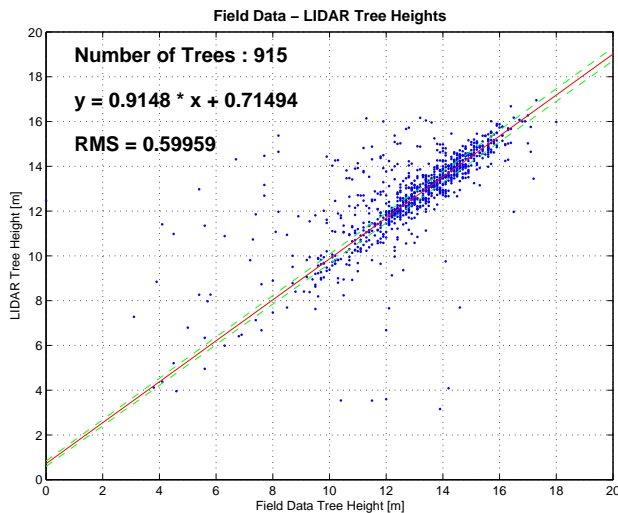


Figure 8: A robust regression of the field measured tree heights against LIDAR derived tree heights is carried out, which uses weights on outliers from the linear model in order to reduce their influence in the fit. Errors for the linear's model coefficients are derived and included as green dashed lines in the graph.

is consistent with previous work and due to the fact that the treetop is not necessarily sampled by the laser scanner.

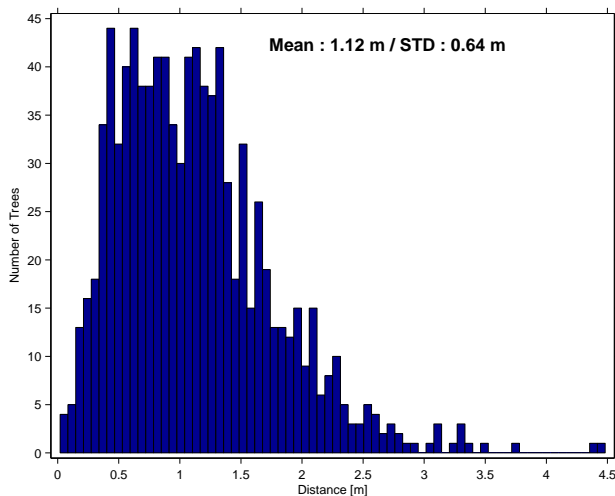


Figure 9: Distribution of distances in between field measured tree positions and the centers of gravity of the clusters. The mean value and the standard deviation are printed in the figure.

As can be seen in Figure 9, the uncertainty in position estimation is much larger than the errors for tree height, with the mean positional offset being as large as 1.12 meters. Since the internal accuracy of the laser point cloud is severely better than that (as can be seen in Table 1), we believe in the main error source are uncertainties in the terrestrial measurements. To a certain amount, the computation of the centers of gravity from the clusters may introduce a positional error, if the segmented cluster is not symmetric.

### 4.3 Reconstruction

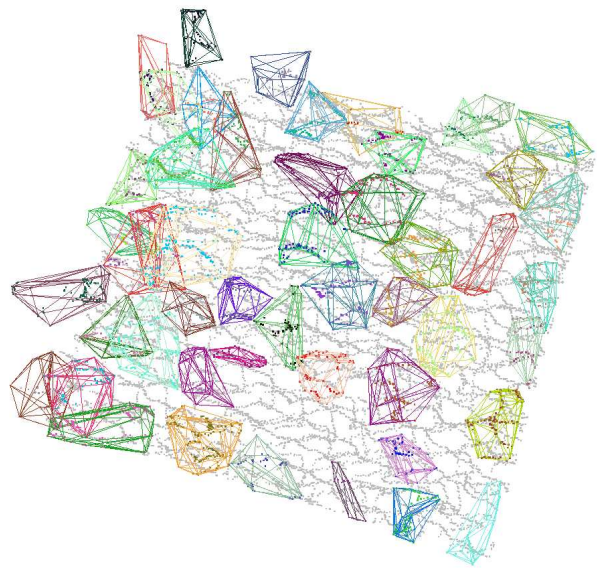


Figure 10: Screen shot of Openscenegraph showing segmented tree crowns as points and their computed convex hull as wire frame. The tool is being used for visual validation of segmentation results, since it allows for real-time interaction and stereo display of the data. Gray points have been classified as ground returns. Only the data from the higher over-flight has been used here.

The most important geometric properties (tree height, position) can be derived directly from the point cloud by finding the maximum value or by computing the center of gravity. However, other properties such as crown diameter or crown volume need a more sophisticated treatment of the point cloud. We have, for instance derived the crown volume by calculating the convex hull for each of the tree clusters as can be seen in Figure 10. In the segmentation process for the area seen in the image, only the data from the higher over-flight has been used, thus we obtain a lesser point density of about  $10 p/m^2$ . Unfortunately, and this seems to be a dilemma of high point density laser scanning approaches, we currently do not have the needed precise field measurement data for validating these crown volume values. Thus we are not showing them here. Additional field work will be done in order to gather some more data on crown properties. First attempts using a self-calibrating photogrammetric reconstruction software developed at the Fraunhofer Institute for Computer Graphics (IGD, Darmstadt) with digital images were not successful. The software relied on some geometrical relationships in the data (parallels, right angles), which is certainly not the case with fuzzy objects such as trees trees.

## 5 CONCLUSIONS

We have shown that it is possible to segment single trees in LIDAR raw data using cluster analysis, if local maxima are chosen as starting positions (seed points). The original raw data is not altered in any way and no information is

lost. Tree heights derived from the segmented clusters are in good agreement with the field data, whereas the locations of the trees do not match as good, which might be due to errors in the field measurements. It is then possible to derive geometric properties such as crown volume or crown diameter on a single tree basis. If a stand-wise approach is desired for a specific application, these values can be aggregated to a larger scale. However, a large number of field inventory trees has not been detected by the automated segmentation. This is due to the special vegetation in the Swiss National Park bearing a lot of "tree clusters", with several stems inside a radius of 1 m. Future work will include developing a seed point algorithm working on the raw data, and the derivation of further geometric crown properties. The feasibility of transferring the algorithm to other vegetation domains containing deciduous trees will be evaluated as well.

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