**Literature**

**LIDAR-based geometric reconstruction of boreal type forest stands at single tree level for forest and wildland fire management** by Felix Morsdorf et al., UZH and WSL, published in Remote Sensing of Environment (2004)

Background

* Remote sensing plays an important role in wildland fire risk assessment, as it is used to estimate physical fuel properties including tree quantity. Size, compactness, and arrangement.
* Structural information may be used as input to fire behavior models. High spatial resolution information is needed to model combustion at the single and sub-tree scale.
* Large-footprint laser scanner data can yield elevation, slope, aspect, canopy height, canopy cover, and canopy bulk density data on the order of 15 to 25 meters.
* Small-footprint laser scanner data can be on the order of 1m with high point density, greater then 10 points per square meter.
* **Two-stage procedure for segmenting single trees** from raw LiDAR point-cloud data is introduced.

Data and Test Site

* Data for this study was from the Ofenpass valley in the Swiss National Park (SNP) featuring boreal forests. 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.
* The TopoSys Falcon II sensor LiDAR data acquired for this study was acquired using a helicopter flying at an altitude of 850m, yielding a point density of 10 p/m2 (first and last reflection from the laser signal was recorded). A smaller subset of the area was imaged at an attitude of 500m yielding a point density of 20 p/m2. Combined, the data point density was >30 p/m2.
* **DSM** created from first reflections; **DTM** created from last reflections.
* Geometric reference targets were placed in the test site and used to evaluate the quality of the LiDAR data. Mean height and position was calculated between known points. Sensor noise was also inferred.

Segmentation

* **K-means segmentation** was performed on the raw 3D point cloud. This clustering algorithm tries to minimize the overall sum of distances between points within a class and their cluster centroids/buoys.
  + Local maxima positions (*seed points)* are derived from DSM, since pine tree crowns are ellipsoidal and horizontally centered. Smoothing filter is applied followed by morphological processing to find pixels that have all 8 neighbors smaller than the center. Kernel size and weights must be tuned for each DSM resolution and expected crown diameter.
* Next, **cluster analysis** is performed stating at the seed locations. Since a Euclidean metric favors ball-shaped clusters, a z-coordinate scaling argument is introduced to accommodate the aspect ratio of pine tree crowns’ height to diameter. (height is 3-6 times greater than crown diameter).
  + Tree height and crown volume are biased toward lower values when point density is reduced (such as for higher flying altitudes) due to under-sampling. Clustering with such large amounts of data is computationally expensive.

Results

* **Geometric properties were derived for each single cluster**, representing a single tree crown.
  + Tree height and position are derived from the maximum z value or computing the center of gravity.
  + Crown diameter was estimated from the segmented point cloud bz dividing the number of returns contained in a cluster by the mean point density, yielding area of crown. Mathematical relation between diameter and circular area.
  + Crown base height was calculated using the 95 percentile of the z-values contained in a cluster. Crown height = tree height – height of base of crown.
  + These parameters were then inputs to a simple geometric tree model to reconstruct the forest stand.
* Comparison to field data (forest inventory information from the WSL) was complicated by the fact that several small tree stems are sometimes close together. Each tree was assigned to the closest LiDAR cluster. The tallest tree within each cluster was used to compute a robust regression.
  + **Robust regression** was used instead of a linear regression due to the presence of outliers in the data due to mismatches between field and LiDAR data.
  + Linear fit of tree height robust regression yielded a slope close to 1 and an offset of 0.98. This **systematic underestimation of tree heights** by the LiDAR data is consistent with previous work, since the laser scanner does not always sample treetops. Underestimation diminishes with higher point density.
  + The tree clumping complicates estimation of crown diameter. Computing the convex hull of the tree group derived an artificial diameter from the field measurements. The regression of field data to LiDAR crown diameter yielded a low adjusted R2 value (0.2), indicating a more or less random relation.
* **Allometric Relationships** were used to assess the feasibility of clustering. A regression of crown diameter and tree height was computed for both LiDAR and field data. The relations for both sets of data were similar.

Conclusions

* The original data was not altered in any way and no information is lost by this method, which processes the point cloud.
* There was good agreement between tree height data from the field and LiDAR data, while crown diameter was not. This may be attributed to the measurement of crown diameter on one side, and crowns may be asymmetric.
* Tree clustering has yielded fewer trees detected from LiDAR compared to field data.
* This technique will probably not work well for deciduous trees, since the seed point extraction relies on trees with 1 well-defined local maximum. Also, older stands of trees with partial crowns will be problematic for allometric relationships.

**3D iterative tree crown delineation in a multi–layered forest using airborne laser scanning** by Hossein Torabzadeh Khorasani, Chapter 3 of thesis, Forest Characterization by Fusion of Imaging Spectroscopy and Airborne Laser Scanning, UZH (2015)

Background

* Most ALS-derived tree detection methods are not accurate for suppressed trees (in the lower strata of multi-layered forests), especially raster-based approaches.
* Point-cloud based methods, supported by newer ALS systems (full-waveform), and hybrid approaches (such as applying k-means clustering to CHM-derived seed points) have been shown to be superior means for estimating single tree parameters.
* This approach utilizes an iterative point cloud-based approach.

Data

* Forested areas in the Dinaric Alps with both single- and multi-layered canopies.
* Forestry inventory data by project NEWFOR, collected in November 2008.
* Full waveform ALS collected in October 2009 with average point density of 30 pt/m2

Methods

* DTM derived from last and single returns.
* 3 parts sequentially and iteratively applied to the ALS point cloud
* Part 1: Segmenation
  + **Horizontal segmentation** (to identify seed points). Normalized point cloud (nPC) is searched for topmost point. All points within the surrounding search radius (set to a value greater than the largest crown in the plot area, derived from forest inventory data) become a subset.
  + **Vertical Layering** (to assess the shape of the tree at height increments). The subset is split into vertical bins, the points in each bin are flattened into a 2D layer. Bin size is determined by the *dh* parameter. Each bin is subjected to density-based clustering method called DBSCAN. Points located within a certain distance threshold, ε, and satisfying a density criterion, *minPts*, are connected. A main cluster, neighboring clusters, and potential outliers based on the criteria are returned. Neighboring clusters are separated from the main cluster by a vertical plane. All other points are removed.
* Part 2: Canopy Stratification
  + Each vertical layer is separated into 3D radial sectors (pie slices) of 60 degrees using the seed point as the origin. This helps to identify smaller suppressed trees. Strata are differentiated based on the size of *gap length*, measured from the forest directly or inferred from experts.
* Part 3: Update the point cloud
  + All points belonging to the identified tree are removed from the point cloud. Updated nPC is returned to the processing chain, ready for delineation of the next tree crown based on the tallest tree height.
  + Iterations follow until all of the points are identified as trees,

**Towards automated characterization of canopy layering in mixed temperate forests using airborne laser scanning** by Reik Leiterer, Hossein Torabzadeh, Reinhard Furrer, Michael Schaepman, and Felix Morsdorf, Forests (2915)

Background

* Canopy structure is the 3D (continuous vertical) distribution of geometric objects and their topology within a forest canopy. Its properties can be described by variables including tree height, tree diameter distribution, or canopy layering.
* LiDAR and ALS systems provide detailed vertical and horizontal information on canopy structure based on active sensing and full-waveform digitization.
* Canopy layer is mainly performed using ABA (Area Base Approaches). Layer thresholds are critical to algorithm performance, and dependent on tree species and forest biome.
* Aims of this study include distinguishing between deciduous and evergreen forest stands.
* Method was tested at the Laegern site, then extended to the entire canton of Aargau.

Methods

* Trees with DBH > 20cm were measured for individual characteristics.
* Canopy layering was estimated for stands. Data was transferred to a raster/grid with 10x10m resolution. Stand maps are available as polygon layers.
* Full waveform ALS data acquired (10 April, 1 August, 2010 for Laegern), (March/April, June/July, 2013 for the Canton of Aargau) for leaf on/off conditions.
* 0.5 x 0.5m DTM generated using last returns for Laegern site to terrain-correct the point cloud.
* Canopy layer was defined as continuous, vertical foliage distribution greater than or equal to 3m in vertical extent. Gaps must also be this size to be considered as separation between canopy layers.
* Distinction between canopies shedding/losing foliage at the end of the growing season (deciduous) OR having leaves throughout the year (evergreen)
* Relative Frequency Distribution (RFD) of echo heights is often displayed as a relative-frequency histogram or pseudo-waveform.
* Canopy ratio was calculated as the length of the topmost canopy layer divided by the total canopy height.
* Using multi-seasonal ALS data, the difference between canopy cover (caused by change in leaf volume) was used as a proxy for canopy type. Deciduous (siginificant differences) and evergreen (non-significant differences) canopies were differentiated.

**Individual Tree Segmentation in Deciduous Forests Using Geodesic Voting** by Matthew Parkan, IGARSS (2015)

Background

**Using remote-sensing data to assess habitat selection of a declining passerine at two spatial scales** by Nica Huber, Felix Kienast, Christian Ginzler, Gilberto Pasinelli . WSL. Landscape Ecology (2016)

doi:10.1007/s10980-016-0370-1

Background

* Studied 3D forest habitat structure for conservation/protection measures for declining species.
* LiDAR remote sensing data used to estimate vegetation height, vertical density and stratification, canopy cover, inclination and solar radiation, as these metrics relate to breeding territories of the wood warbler bird.

Methods - LiDAR

* The data used consisted of first and last return LiDAR data, DTM and DSM. nDSM created by subtracting DTM from DSM.
* Mean point density was 1.5-2 m with a standard deviation in height accuracy of 1.5m. nDSM values deviating negatively by three or more times the standard deviation were treated as outliers and excluded from the analysis.
* Brandtberg et al. 2003

**The Suitability of Leaf-off Airborne Laser Scanning Data in an Area-based Forest Inventory of Coniferous and Deciduous Trees** by Maria Villikka, Petteri Packalén and Matti Maltamo, Finnish Forest Research Institute (2011)

* Studied the separation of deciduous and coniferous trees from ALS data collected under leaf-off conditions.
* Area-based approach used (which is based on the height and distribution of ALS points), as opposed to an individual tree delineation approach (in which individual trees are identified from high resolution ALS data with multiple laser points per square meter. Tree characteristics on the tree level are then combined to get estimates on the order of stands).
* Forest inventory data is typically collected during leaf-on conditions over the summer, while leaf-off data is preferred for terrain modeling.

**Deciduous-coniferous tree classification using difference between first and last pulse laser signatures** by Liang et al., Finnish Geodetic Institute, published in IAPRS (2007)

* Deciduous-coniferous classification method using only laser scanning data.
* Leaf-off data collected with a point density of 4-5 pulse per square meter. (Leaf-off data is commonly collected to get the highest accuracy possible in the DTM.)
* DTM and DSM both created (using last and first/highest returns, respectively) using 0.5m grid spacing. CHM created by subtracting DTM from DSM.
* Treetop detection done similar to Hyyppä et al ([2001](http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=921414)) – a raster-based approach with 3 steps.

1. Prefiltering done with a lowpass 3x3 convolution filter.
2. Seed point extraction to find local maxima (defined by Hyyppä et al. as points where the diffused image has values greater than any of its eight neighbors). Liang used a 5x5 maximum filter. Lower local maxima than 3m were not included.
3. Seeded region growing.

* Liang et al. assumed a reduced tree radius, and claims that the difference in first-last pulses within the crown center is a reliable indicator of deciduous vs. coniferous.
* Species were classified based on the proportion of pixels within the estimated crown area with a significant height difference (deciduous) versus no significant difference (coniferous).
* Reasons for misclassification include:
  + Branch structure – the basic assumption for this method is that for leaf-off conditions, the last pulse would penetrate deciduous tree crowns and reflected from coniferous treetops. *For deciduous trees, denser crowns reflect last pulses more from upper branches, which reduces the first-last pulse difference and leads to misclassification.*

**To read:**

Rahman and Gorte (2009)

Li et al. (2012), Ferraz et al. (2012)

Parkan (2015)

Transferrable approach: Wulder,M.A.;Coops,N.C.;Hudak,A.T.;Morsdorf,F.;Nelson,R.;Newnham,G.;Vastaranta,M. Status and prospects for LiDAR remote sensing of forested ecosystems. Can. J. Remote Sens. 2013, 39, S1–S5.

**Explaining the big picture to people who aren’t familiar with the field of remote sensing:**

Light detection and ranging (lidar) is an active remote sensing technology. It differs from passive systems (such as multispectral cameras that measure incoming light origination outside of the system) because it sends out pulses of laser light. By measuring the time it takes each pulse to return after interacting with and reflecting off of objects in its path, the range or distance to an object can be calculated. This generates three-dimensional data with high resolution and accuracy. (Li et al., 2012)

Lidar technology is used for a variety of applications.

In remote sensing, lidar systems are commonly integrated into aircrafts to form airborne laser scanning (ALS) systems. From ALS data, widespread imaging of forests is enabled.

Forest inventorying is traditionally done manually using instruments on the ground, or by a form of visual inspection using aerial photography. Segmenting individual trees and deriving structural measurements for them is io