Tree detection using aerial LiDAR

Yu-Lun Wu
1.1 Motivation

- Forest:
  - Improve decision-making of logging operations
  - Biomass and biodiversity and greenhouse gas emission assessment
  - Monitor forest regeneration
  - Tree detection is a step before extracting individual tree structure parameters (e.g., tree height, crown height, crown size, leaf area index)

- Urban:
  - Change detection in monitoring the growth of urban trees [Xiao et al., 2016]

- Why LiDAR:
  - Fast data acquisition with relatively high accuracy
  - Capability of showing the detailed structure of vegetation (Provide information beneath the upper-most surface of canopy)
1.2 Problems

- **LiDAR data acquisition**
  - Occlusion by upper canopies
  - Stems are hard to be seen from nadir-view
  - Laser pulses can be perturbed on its own path through the canopies (especially for full waveform LiDAR, this can make it hard to interpret the returned full waveform signals)
  - Weather conditions, such as fog, rain, and mist attenuate the laser signals
  - Spatiotemporal uncertainties due to the influence of the scan-angle on the recorded signal intensity

- **Segmentation**
  - Trees are usually over/under-segmented by the algorithm
  - Detailed structures cannot be shown with sparse ALS (aerial laser scanning) data (low point density)
1.3 Assumptions

- **Data acquisition**
  - Stems are hard to be seen from nadir-view
  - A semi-dense (4-8 pulses/m²), leaf-on LiDAR data is capable for crown detection. [Korpela et al., 2007]

- **Full waveform LiDAR**
  - Full waveform LiDAR transmitted pulses and the returned signals are Gaussian type [Reitberger et al., 2006]

- **Algorithm**
  - Taller trees have larger crown diameters [Li et al., 2012]
  - Treetops are typically located around the center of crowns [Chen et al., 2006]
2 Overview

Urban

Change detection of the trees
- [Hebel et al., 2013]
- [Xiao et al., 2016]

Forest

Dead and fallen trees
- LiDAR and aerial image
  - [Polewski, 2017]
- Discrete return
- First/last pulse
- Full-waveform
  - 3D segmentation
    - [Reiberger et al., 2009]

Living trees

Living trees
- Individual tree growing segmentations
  - [Li et al., 2012]
- Adaptive clustering
  - [Lee et al., 2010]
- Watershed+ distance transformed image
  - [Chen et al., 2006]
3.1 Method 1 (1)

Title: Isolating individual trees in a savanna woodland using small footprint lidar data [Chen et al., 2006]

- Create DEM & CHM
- Create CMM from CHM with variable window size
- Gaussian filter to smooth CMM
- Treetop detection with CMM
- Watershed segmentation with CMM
- Segmentation with distance-transformed image

Modified from [Chen et al., 2006]

| ● DEM: digital elevation model |
| ● CHM: canopy height model |
| ● CMM: canopy maximum model |
3.1 Method 1 (2)

☐ Create DEM and CHM
  - DEM (digital elevation model)
    - Extract the lowest last lidar return points in each grid, with some interpolation techniques to generate the terrain model
  - CHM (canopy height model)
    - Extract the highest first return points in each grid to generate the elevation model of the canopy height (subtract the terrain height, purely canopy height)

☐ CMM, Gaussian filter and treetop detection
  - CMM (canopy maximum model)
    - Record the maximum laser height within its neighborhood
    - Filter CHM with variable window sizes to generate CMM
3.1 Method 1 (3)

- CMM, Gaussian filter and treetop detection (continue)
  - Gaussian filter
    - Smooth the CMM
    - Suppress irrelevant local maxima in treetop detection (because a segment can only contain one treetop marker, too many treetop markers would lead to wrongly and over-segmentation)
  - Variable Window Sizes
    - Assume taller trees have larger crown sizes (assign larger window size)
    - Decided by lower-limit of the prediction intervals of the regression curve of crown size and tree height
  - Treetop detection
    - Local maxima in CMM are marked as treetops

[Chen et al., 2006]
3.1 Method 1 (4)

- **Watershed segmentation with CMM**
  - Watershed segmentation
    1. Flip the CMM model (calculate the complement of CMM)
    2. Pour in water and build the dam at the boundary (The boundary of the segments is where the edges of water finally meet when gradually filling water. In other words, the boundary of the segments is the curve of local minimum of the canopy maximum model)
    3. Marker-controlled watershed segmentation (the segmentation result which does not contain any treetop marker would be merged to another segment)

Fig: Watershed segmentation

[Chen et al., 2006]
### 3.1 Method 1 (5)

- **Segmentation with distance-transformed image**
  - Treetop is hard to be detected from the flat oak canopy in CHM or CMM, so the distance transformed image is applied to find the treetops.
  - **Steps:**
    1. Binary image created: canopy assigned the value 1; background and watershed lines assigned the value 0
    2. Use **distance-transformed image** (after h-minima) to find treetops
      - **DTI**: distance to the closest boundary in the binary image
      - Use h-minima as a threshold to suppress all local minima shallower than h (h-minima transformation)
    3. Marker-controlled watershed segmentation
    4. Remove all segments which are shorter than 2 m (dead trunks and science instrument)
3.1 Method 1 (6)

- Segmentation with distance-transformed image (continue)

Fig: Binary Image and distance-transformed image

- h-minimum: suppress all elements shallower than a specific value
  - Example: suppress all elements shallower than 4

```matlab
b = immin(a,4)
```

[Chen et al., 2006]
Title: 3D segmentation of single trees exploiting full waveform LIDAR data [Reiberger et al., 2009]

- **Watershed segmentation with CHM**
- **Stem detection**
- **Normalized cut segmentation**

Modified from [Reiberger et al., 2009]
3.2 Method 2 (2)

- **Watershed segmentation with CHM (canopy height model)**
  - Steps: (similar to the previous process, but apply on CHM instead of CMM)
    1. Extract the highest 3D points in the cells
    2. Correct the heights of the points with DTM (normalization)
    3. Create and smooth CHM with bilinear interpolation to avoid over-segmentation
    4. Implement watershed segmentation
  - The local maxima define possible tree positions (treetop detection)
  - Smaller trees in the intermediate and lower height level cannot be recognized since they are not visible in the CHM (Canopy height model only shows the canopy surfaces, no information underneath)

- **Stem detection**
  - Separate neighboring trees from forming a tree group
  - Improve the accuracy of the detected tree position
  - Improve the detection rate in the intermediate and upper tree layers
3.2 Method 2 (3)

- Stem detection (continue)
  - Steps:
    1. Separate data points in a single segment (from watershed segmentation) into ground, stem and crown points
      - Ground points are points lower than 1m high respect to DTM
      - Divided into stem points and crown points by finding an appropriate crown base height
    2. The potential stem points are assigned to a cluster according to their horizontal distance (Euclidian distance); merge the clusters based on their distance until reach a predefined number of clusters
    3. Apply RANSAC-based 3D line adjustment to find tree stems (link the clusters), 3D lines with incident angle larger than 7 degrees are not considered as tree stems
3.2 Method 2 (4)

- Stem detection (continue)
  
  In the center segment in the right figure, the 3 yellow crosses are the detected stems. We can find that they are consistent to the ground truth (white points). While the local maximum is not good enough to represent the possible stem positions and it underestimated possible number of trees.
3.2 Method 2 (5)

- **Normalized cut segmentation**
  - Goal: Divide the segments according to voxel similarities
    - Similarity is basically based on the distances in different direction components and can additionally be based on the waveform properties
  - Steps:
    1. Subdivide the region of interest into a voxel structure (Fig. 9a- see next page)
    2. Maximize the similarity of the segment members (members inside the segment) and minimize the similarity between two adjacent segments
      - Minimize the cost function $\rightarrow$ eigenvalue problem

$$ NCut(A, B) = \frac{\text{Cut}(A, B)}{\text{Assoc}(A, V)} + \frac{\text{Cut}(A, B)}{\text{Assoc}(B, V)} $$

- Find the solution of the eigenvalue problem
- Binarize the solution with a threshold. Cut the graph into two new graphs

**Warning!!** Complicated
3.2 Method 2 (6)

- Normalized cut segmentation (continue)
  3. Repeat the segmentation disjointing steps ①② until the similarity is above the threshold
  3. Remove segmentations which do not meet criteria

- Figure for illustration of voxels and segmentation division

*Fig. 9.* (a) Subdivision of the ROI into a voxel structure and (b) division into tree segments.

[Reiberger et al., 2009]
3.3 Method 3 (1)

Title: A new method for segmenting individual trees from the lidar point cloud [Li et al., 2012]

**Region growing on raw point data**

**Preprocessing**
- Separate ground/ above-ground LiDAR points
  - Ground points $\rightarrow$ DEM (digital elevation model)
  - Above-ground points $\rightarrow$ Tree data points
- Normalize the height to remove the topography

**Segmentation**
- Region growing segmentation based on point spacing and the 2D projection of the tree shape

Modified from [Li et al., 2012]
3.3 Method 3 (2)

- **Algorithm for segmentation**
  - Based on 2D Euclidean distances between points (horizontal distance between 2 points)
  - Process the data points globally from top to bottom (all points haven’t been assigned to a segment would be calculated and classified whether it belong to this new segment or not, from the upper most point to the bottom points)
  - Apply adaptive threshold for local maximum points classification (to tell whether this local maximum is another treetop or a branch of this tree. If the distance is smaller than the threshold, the point would be classified as a point belonging to the segment, vice versa. See next page for figures)
    - Assume higher trees have wider crown
      - For points higher than 15m: threshold = 2m
      - For points lower or equal to 15m: threshold = 1.5m
3.3 Method 3 (3)

- **Algorithm for segmentation**
  - Illustration for horizontal distance
  - We process points from top to bottom: B -> C -> D ...

![Diagram showing tree segmentation with distances labeled](image)

Figure 4. The spacing between points on two trees. [Li et al., 2012]
3.3 Method 3 (4)

- **Algorithm for segmentation**
  - **For local maximum:**
    - If \( \text{dist.}(u, \text{closet pt. in segment}) > \text{threshold} \), \( u \notin \text{the segment} \)
    - If \( \text{dist.}(u, \text{closet pt. in segment}) \leq \text{threshold} \), and \( u \) is **closer** to the closet point in the segment than the closet point not in the segment, \( u \in \text{the segment} \)
    - If \( \text{dist.}(u, \text{closet pt. in segment}) \leq \text{threshold} \), and \( u \) is **farther** to the closet point in the segment than the closet point not in the segment, \( u \notin \text{the segment} \)
  - **Other points:**
    - If \( \text{dist.}(u, \text{closet pt. in segment}) \leq \text{dist.}(u, \text{closet pt. not in segment}) \), \( u \in \text{the segment} \)
  - **Process the points which do not belong to any segment yet from top to bottom again** (iterate the process to form the 2nd segment and more)

\( u \): the point to be classified

\( \text{dist.}(A,B) \) means the distance between \( A, B \)

Note: horizontal distance

View from above
Title: Isolating individual trees in a savanna woodland using small footprint lidar data [Chen et al., 2006]

- Study area: Ione, California (Lon: 120.57 °W; Lat.: 38.26 °N)
- Vegetation type: Oak savanna woodland (scattered blue oaks, gray pines (minor))
- Acquired time: 24th, Aug. 2003
- Instrument: Optech ALTM
  - First/last return pulses
- Mapping
  - Flying altitude: 500m
  - Swath width: 300m
  - Z-shape scanning path
  - Area scanned twice
  - Footprint size: 18cm
  - Ave. point density: 9.5 pt/ m²

Figure 1. A CASI image covering the study area. [Chen et al., 2006]
4.1 Data 1 (2)

○ Accuracy: vertical 18cm, horizontal 1/3000 of flying height

☐ Selected area size: 800m x 800m

☐ Reference data

○ Two 100m x 300m transects

○ Manually delineate in CHM with the aid of aerial photos

○ 772 trees in two transects
4.2 Data 2 (1)

Title: 3D segmentation of single trees exploiting full waveform LIDAR data [Reiberger et al., 2009]

- Study area: Bavarian Forest National Park, Germany
- Forest type: mixed mountain forests (Norway spruce, European beech dominant)
  - Selected plots: 18 sample plots (1000 m² – 3600 m² each)
- 2 types of LiDAR: First/last pulses (TopoSys), full waveform (Riegl)

<table>
<thead>
<tr>
<th>Dataset</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Foliage</td>
<td>Leaf-on</td>
<td>Leaf-off</td>
<td>Leaf-on</td>
<td>Leaf-on</td>
</tr>
<tr>
<td>Instrument</td>
<td>TopoSys Falcon II</td>
<td>Riegl LMS-Q560</td>
<td>Riegl LMS-Q560</td>
<td>Riegl LMS-Q560</td>
</tr>
<tr>
<td>Pts/m²</td>
<td>10</td>
<td>25</td>
<td>25</td>
<td>10</td>
</tr>
<tr>
<td>Ave. flying height (m)</td>
<td>850</td>
<td>400</td>
<td>400</td>
<td>500</td>
</tr>
<tr>
<td>Footprint (cm)</td>
<td>85</td>
<td>20</td>
<td>20</td>
<td>25</td>
</tr>
</tbody>
</table>

Table: details of datasets

Modified from [Reiberger et al., 2009]
4.2 Data 2 (2)

- Reference data
  - Trees with DBH (diameter at breast height) > 10 cm are collected
  - Trees are categorized into 3 layers: lower, intermediate or upper based on the tree heights
  - DTM acquired in 2003 with LiDAR data
4.3 Data 3 (1)

Title: A new method for segmenting individual trees from the lidar point cloud [Li et al., 2012]

- Study area: Sierra National Forest, California (118 km²)
  - Forest type: Conifer dominant
- Instrument: Optech GEMINI Airborne Laser Terrain Mapper (ALTM)
  - Discrete return (recorded up to 4 echoes/ pulse)
- Mapping:
  - Ave. flying height: 700 m
  - Ave. swath width: 509.56 m, overlap: 341.4 m
  - All of the ground area was covered by 3 swaths
  - Target point density: > 6 points/ m²
  - Accuracy: vertical 5-10 cm, horizontal 1:11,000 of flying height
4.3 Data 3 (2)

- **Selected data:**
  - 20 circular plots selected (12.62 m in radius)
  - Number of trees in one plot: 9-35 (ave. 19)

- **Reference data**
  - Geo-reference the tree locations with GPS
  - Referenced trees manually verified with LiDAR point cloud in ArcScene
  - 380 reference trees in total

Figure 1. Study area and testing plots. [Li et al., 2012]
5.1 Result 1

Title: Isolating individual trees in a savanna woodland using small footprint lidar data [Chen et al., 2006]

- Accuracy assessment
  - Absolute accuracy for tree isolation (AATI):
    \[
    \text{AATI} = \frac{\text{number of crowns that correspond to the ground truth}}{\text{number of crowns in the field}}
    \]
  - With overlaying range 90-110% of reference polygon considered as matched

- Best result
  - AATI = 64.1%, with parameters value setting \( \alpha = 0.01 \), \( h = 0.5\text{m} \)

\( \alpha \): regarding the Gaussian filter size for smoothing CMM
\( h \): h-minima transform in the distance-transformation image
Title: 3D segmentation of single trees exploiting full waveform LIDAR data [Reiberger et al., 2009]

- **Overall detection rate:**
  
  \[
  \text{detection rate} = \frac{\text{number of detected trees that correspond to ref. trees}}{\text{number of ref. trees}}
  \]

### Result with dataset 2: leaf-off, full waveform

<table>
<thead>
<tr>
<th>Method</th>
<th>Detection rate %</th>
<th>False positive</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Watershed</td>
<td>5 L 21 M 77 U 48</td>
<td>4%</td>
<td>Poor in lower layer because most of the trees are tall</td>
</tr>
<tr>
<td>Watershed + stem detection</td>
<td>7 L 27 M 82 U 52</td>
<td>5%</td>
<td>Improved intermediate and upper layers; Higher accuracy of tree locations</td>
</tr>
<tr>
<td>Watershed + stem detection + normalized cut</td>
<td>21 L 38 M 87 U 60</td>
<td>9%</td>
<td>Improved lower and intermediate layer about 16%</td>
</tr>
</tbody>
</table>

- **Impact of full waveform data in detection rate**
  - Increase 5% in watershed method
  - Increase 10% in normalized cut segmentation
5.3 Result 3 (1)

Title: A new method for segmenting individual trees from the lidar point cloud [Li et al., 2012]

- 2 scenarios:
  - Dense plot (c): not fully segmented
  - Sparse plot (d): correctly detected and segmented

- Overall:
  - 380 trees in 20 plots, 347 trees are segmented
  - 53 trees missed, 20 trees falsely detected

Fig: Segmentation results
5.3 Result 3 (2)

- **Accuracy assessment in each plot**
  - Overall detection rate: \( \frac{327}{380} = 0.86 \)

<table>
<thead>
<tr>
<th>Plot ID</th>
<th>Number of trees</th>
<th>Density (trees/m²)</th>
<th>Number of segmented trees</th>
<th>TP</th>
<th>FP</th>
<th>FN</th>
<th>r</th>
<th>p</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>14</td>
<td>0.03</td>
<td>14</td>
<td>13</td>
<td>1</td>
<td>1</td>
<td>0.93</td>
<td>0.93</td>
<td>0.93</td>
</tr>
<tr>
<td>2</td>
<td>9</td>
<td>0.02</td>
<td>11</td>
<td>9</td>
<td>2</td>
<td>0</td>
<td>1.00</td>
<td>0.82</td>
<td>0.90</td>
</tr>
<tr>
<td>3</td>
<td>21</td>
<td>0.04</td>
<td>20</td>
<td>19</td>
<td>1</td>
<td>2</td>
<td>0.90</td>
<td>0.95</td>
<td>0.93</td>
</tr>
<tr>
<td>4</td>
<td>15</td>
<td>0.03</td>
<td>13</td>
<td>13</td>
<td>0</td>
<td>2</td>
<td>0.87</td>
<td>1.00</td>
<td>0.93</td>
</tr>
<tr>
<td>5</td>
<td>22</td>
<td>0.04</td>
<td>21</td>
<td>20</td>
<td>1</td>
<td>2</td>
<td>0.91</td>
<td>0.95</td>
<td>0.93</td>
</tr>
<tr>
<td>6</td>
<td>24</td>
<td>0.05</td>
<td>21</td>
<td>21</td>
<td>0</td>
<td>3</td>
<td>0.88</td>
<td>1.00</td>
<td>0.93</td>
</tr>
<tr>
<td>7</td>
<td>17</td>
<td>0.03</td>
<td>16</td>
<td>15</td>
<td>1</td>
<td>2</td>
<td>0.88</td>
<td>0.94</td>
<td>0.91</td>
</tr>
<tr>
<td>8</td>
<td>16</td>
<td>0.03</td>
<td>20</td>
<td>16</td>
<td>4</td>
<td>0</td>
<td>1.00</td>
<td>0.80</td>
<td>0.89</td>
</tr>
<tr>
<td>9</td>
<td>12</td>
<td>0.02</td>
<td>13</td>
<td>11</td>
<td>2</td>
<td>1</td>
<td>0.92</td>
<td>0.85</td>
<td>0.88</td>
</tr>
<tr>
<td>10</td>
<td>31</td>
<td>0.06</td>
<td>23</td>
<td>23</td>
<td>0</td>
<td>8</td>
<td>0.74</td>
<td>1.00</td>
<td>0.85</td>
</tr>
<tr>
<td>11</td>
<td>21</td>
<td>0.04</td>
<td>19</td>
<td>19</td>
<td>0</td>
<td>2</td>
<td>0.90</td>
<td>1.00</td>
<td>0.95</td>
</tr>
<tr>
<td>12</td>
<td>13</td>
<td>0.03</td>
<td>13</td>
<td>12</td>
<td>1</td>
<td>1</td>
<td>0.92</td>
<td>0.92</td>
<td>0.92</td>
</tr>
<tr>
<td>13</td>
<td>16</td>
<td>0.03</td>
<td>14</td>
<td>13</td>
<td>1</td>
<td>3</td>
<td>0.81</td>
<td>0.93</td>
<td>0.87</td>
</tr>
<tr>
<td>14</td>
<td>21</td>
<td>0.04</td>
<td>18</td>
<td>17</td>
<td>1</td>
<td>4</td>
<td>0.81</td>
<td>0.94</td>
<td>0.87</td>
</tr>
<tr>
<td>15</td>
<td>35</td>
<td>0.07</td>
<td>25</td>
<td>25</td>
<td>0</td>
<td>10</td>
<td>0.71</td>
<td>1.00</td>
<td>0.83</td>
</tr>
<tr>
<td>16</td>
<td>23</td>
<td>0.05</td>
<td>19</td>
<td>19</td>
<td>0</td>
<td>4</td>
<td>0.83</td>
<td>1.00</td>
<td>0.90</td>
</tr>
<tr>
<td>17</td>
<td>16</td>
<td>0.03</td>
<td>15</td>
<td>14</td>
<td>1</td>
<td>2</td>
<td>0.88</td>
<td>0.93</td>
<td>0.90</td>
</tr>
<tr>
<td>18</td>
<td>17</td>
<td>0.03</td>
<td>16</td>
<td>15</td>
<td>1</td>
<td>2</td>
<td>0.88</td>
<td>0.94</td>
<td>0.91</td>
</tr>
<tr>
<td>19</td>
<td>20</td>
<td>0.04</td>
<td>17</td>
<td>17</td>
<td>0</td>
<td>3</td>
<td>0.85</td>
<td>1.00</td>
<td>0.92</td>
</tr>
<tr>
<td>20</td>
<td>17</td>
<td>0.03</td>
<td>19</td>
<td>16</td>
<td>3</td>
<td>1</td>
<td>0.94</td>
<td>0.84</td>
<td>0.89</td>
</tr>
</tbody>
</table>

Overall: 380 trees, 347 segmented, 327 correctly detected.

[Li et al., 2012]
6.1 Discussion 1

Title: Isolating individual trees in a savanna woodland using small footprint lidar data [Chen et al., 2006]

- Old and large oak trees usually lead to over-segmentation due to their out-reaching and irregular branches
- It is difficult to separate trees with different heights but growing closely
- The segmentation accuracy increased about 10% after applying distance-transformed image for segmentation
- Low local minimum suppression leads to over-segmentation
6.2 Discussion 2

Title: 3D segmentation of single trees exploiting full waveform LIDAR data [Reiberger et al., 2009]

- A combination of normalized cut segmentation with watershed segmentation and stem detection provides the best results
- Higher detection rate for the leaf-off dataset in the lower and intermediate layers because of the higher penetration of the deciduous trees in the leaf-off situation
- Full waveform data improved the detection rate compared to first/last pulse data because it represents the tree shape more precisely
- Point density higher than 10 pts/m² does not improve the detection rate considerably
- Features (intensity and pulse width) in full waveform data can be used to improve Ncut segmentation
- Although the overall detection rate is only 60%, but the detection rate for the upper layer reached 87% for dataset 2.
6.3 Discussion 3

Title: A new method for segmenting individual trees from the lidar point cloud [Li et al., 2012]

- Generally, the number of trees is under-estimated
- The algorithm has to be evaluated whether it is also applicable to delineate deciduous forests
- Traditional methods apply tree top detection, the search window size affects the detection accuracy. This algorithm finds the global maximum as a starting point for clustering to avoid this problem.
- Tree segmentation uncertainty is mainly influenced by spacing threshold, it is hard to be decided in dense forests (solution: apply adaptive threshold based on the tree height)
7 Opinion (1)

- General
  - Due to the data differences, it is hard to compare the results
  - A single tree detection algorithm is not suitable for every forest type

- Methods
  - Although method 2 only has the 60% overall detection rate, however, it shows a high detection rate in the upper layer
  - Both method 1 and 3 cannot detect trees that are underneath a taller tree
  - The collection of reference data influenced the resulted detection rate (in method 1 the reference data is derived from canopy height model, the trees at the lower and intermediate layers were not counted. This leads to a false high detection rate)

- Other approaches:
  - Combine aerial images and LiDAR data
<table>
<thead>
<tr>
<th>Method</th>
<th>Method 1</th>
<th>Method 2</th>
<th>Method 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Detection rate</td>
<td>64.1%</td>
<td>60%</td>
<td>86%</td>
</tr>
<tr>
<td>Description</td>
<td>Watershed, distance-transform</td>
<td>Watershed, stem detection, Ncut</td>
<td>Region-growing</td>
</tr>
<tr>
<td>Tree type</td>
<td>Scattered blue oaks, gray pine</td>
<td>Norway spruce, European beech</td>
<td>Conifer dominant</td>
</tr>
<tr>
<td>Remarks</td>
<td>-</td>
<td>87% detection rate in the upper layer</td>
<td>-</td>
</tr>
</tbody>
</table>
Reference (1)


Reference (2)

- Polewski P P (2017) Reconstruction of standing and fallen single dead trees in forested areas from LiDAR data and aerial imagery. PhD Dissertation, Department of Architecture, Technische Universität München, 2017


### Tree shapes

<table>
<thead>
<tr>
<th>Method</th>
<th>Method 1</th>
<th>Method 2</th>
<th>Method 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Description</td>
<td>Watershed, distance-transform</td>
<td>Watershed, stem detection, Ncut</td>
<td>Region-growing</td>
</tr>
<tr>
<td>Tree type</td>
<td>Scattered blue oaks, gray pine</td>
<td>Norway spruce, European beech</td>
<td>Conifer dominant</td>
</tr>
</tbody>
</table>

- Gray pine: [https://www.conifers.org/pi/Pinus_sabiniana.php](https://www.conifers.org/pi/Pinus_sabiniana.php)