Automatic construction of 3D tree models from airborne LiDAR data in multiple levels of detail

Geert Jan (Rob) de Groot

Supervisors:
Prof. dr. Jantien Stoter
Dr. Hugo Ledoux
Introduction

Methodology

Results

Conclusions

Goal

3dfier output (3D Geoinformation Group, 2019)
Goal
Goal
Goal
How can 3D tree models at varying Levels of Detail be automatically constructed from airborne LiDAR point cloud data?
Research Questions

How can 3D tree models at varying Levels of Detail be automatically constructed from airborne LiDAR point cloud data?

1. What applications require what type or Level of Detail (LOD) of 3D tree models?

2. What LODs are most fitting for which type of tree models (single vegetation object or vegetation group)?

3. How can a final implementation be made to fit into the 3dfier pipeline?

4. Is it possible to determine which tree type a tree belongs to, based on features that can be extracted from trees in airborne LiDAR point cloud data?
Approach

Classification

Segmentation

Data-cleaning

Modelling

Tree-type Classification
### Proposal

<table>
<thead>
<tr>
<th>LOD</th>
<th>LOD x.0</th>
<th>LOD x.1</th>
<th>LOD x.2</th>
<th>LOD x.3</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOD0</td>
<td><img src="image1" alt="LOD0.0" /></td>
<td><img src="image2" alt="LOD0.1" /></td>
<td><img src="image3" alt="LOD0.2" /></td>
<td><img src="image4" alt="LOD0.3" /></td>
</tr>
<tr>
<td>LOD1</td>
<td><img src="image5" alt="LOD1.0" /></td>
<td><img src="image6" alt="LOD1.1" /></td>
<td><img src="image7" alt="LOD1.2" /></td>
<td><img src="image8" alt="LOD1.3" /></td>
</tr>
<tr>
<td>LOD2</td>
<td><img src="image9" alt="LOD2.0" /></td>
<td><img src="image10" alt="LOD2.1" /></td>
<td><img src="image11" alt="LOD2.2" /></td>
<td><img src="image12" alt="LOD2.3" /></td>
</tr>
<tr>
<td>LOD3</td>
<td><img src="image13" alt="LOD3.0" /></td>
<td><img src="image14" alt="LOD3.1" /></td>
<td><img src="image15" alt="LOD3.2" /></td>
<td><img src="image16" alt="LOD3.3" /></td>
</tr>
</tbody>
</table>

**LOD Specifications (Biljecki et al., 2016)**

---

**Introduction**

**Methodology**

**Results**

**Conclusions**
## Proposal

<table>
<thead>
<tr>
<th>LODx.A</th>
<th>LODx.B</th>
<th>LODx.C</th>
<th>LODx.D</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOD0.0</td>
<td>LOD0.1</td>
<td>LOD0.2</td>
<td>LOD0.3</td>
</tr>
<tr>
<td></td>
<td>LOD1.0</td>
<td>LOD1.1</td>
<td>LOD1.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LOD2.0</td>
<td>LOD2.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>LOD3.0</td>
</tr>
</tbody>
</table>

LOD Proposal (Ortega-C’ordova, 2018)
Proposal

**Methodology**

- LOD0
- LOD1
- LOD2
- LOD3.0
- LOD3.1
Classification

Introduction

Methodology

Results

Conclusions

Actueel Hoogtebestand Nederland

Height from ground

Planarity

Ruggedness
Classification
Watershed segmentation (Roudier et Al., 2008)
Segmentation

Watershed segmentation (Roudier et Al., 2008)
Segmentation

**DEM**

**Segmented DEM**

2m

15m
Segmentation
Segmentation

- **Good**
- **Under**
- **Over**
## Segmentation

<table>
<thead>
<tr>
<th>DEM resolution</th>
<th>Underseg.</th>
<th>Overseg.</th>
<th>Good segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.25m</td>
<td>4.3%</td>
<td>20.6%</td>
<td>75.0%</td>
</tr>
<tr>
<td>0.50m</td>
<td>10.6%</td>
<td>8.6%</td>
<td>80.8%</td>
</tr>
<tr>
<td><strong>0.75m</strong></td>
<td><strong>12.5%</strong></td>
<td><strong>4.0%</strong></td>
<td><strong>83.6%</strong></td>
</tr>
<tr>
<td>1.00m</td>
<td>13.3%</td>
<td>3.4%</td>
<td>83.2%</td>
</tr>
<tr>
<td>1.25m</td>
<td>17.3%</td>
<td>1.2%</td>
<td>81.4%</td>
</tr>
<tr>
<td>1.50m</td>
<td>18.5%</td>
<td>2.3%</td>
<td>79.3%</td>
</tr>
</tbody>
</table>
## Results

<table>
<thead>
<tr>
<th>Threshold</th>
<th>Trees recognized</th>
<th>Underseg.</th>
<th>Overseg.</th>
<th>Good segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.00m</td>
<td><strong>91.6%</strong></td>
<td>9.1%</td>
<td>7.7%</td>
<td>83.2%</td>
</tr>
<tr>
<td>1.10m</td>
<td>89.7%</td>
<td>10.4%</td>
<td>6.7%</td>
<td>82.9%</td>
</tr>
<tr>
<td>1.20m</td>
<td>88.0%</td>
<td>11.2%</td>
<td>5.7%</td>
<td>83.1%</td>
</tr>
<tr>
<td>1.30m</td>
<td>85.7%</td>
<td>12.3%</td>
<td>4.5%</td>
<td>83.2%</td>
</tr>
<tr>
<td>1.40m</td>
<td><strong>84.5%</strong></td>
<td>12.5%</td>
<td>3.7%</td>
<td><strong>83.8%</strong></td>
</tr>
<tr>
<td>1.50m</td>
<td>82.8%</td>
<td>12.5%</td>
<td>4.0%</td>
<td>83.6%</td>
</tr>
<tr>
<td>1.60m</td>
<td>81.8%</td>
<td>12.6%</td>
<td>3.2%</td>
<td>84.2%</td>
</tr>
<tr>
<td>1.70m</td>
<td>81.8%</td>
<td>12.6%</td>
<td>3.2%</td>
<td>84.2%</td>
</tr>
<tr>
<td>1.80m</td>
<td>81.3%</td>
<td>13.3%</td>
<td>3.5%</td>
<td>83.2%</td>
</tr>
<tr>
<td>1.90m</td>
<td>80.6%</td>
<td>13.1%</td>
<td>2.2%</td>
<td><strong>84.6%</strong></td>
</tr>
<tr>
<td>2.00m</td>
<td>79.9%</td>
<td>13.5%</td>
<td>2.2%</td>
<td>84.2%</td>
</tr>
</tbody>
</table>
## Segmentation

<table>
<thead>
<tr>
<th>Threshold</th>
<th>Trees recognized</th>
<th>Underseg.</th>
<th>Overseg.</th>
<th>Good segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.00m</td>
<td>91.6%</td>
<td>9.1%</td>
<td>7.7%</td>
<td>83.2%</td>
</tr>
<tr>
<td>1.10m</td>
<td>89.7%</td>
<td>10.4%</td>
<td>6.7%</td>
<td>82.9%</td>
</tr>
<tr>
<td>1.20m</td>
<td>88.0%</td>
<td>11.2%</td>
<td>5.7%</td>
<td>83.1%</td>
</tr>
<tr>
<td>1.30m</td>
<td>85.7%</td>
<td>12.3%</td>
<td>4.5%</td>
<td>83.2%</td>
</tr>
<tr>
<td>1.40m</td>
<td><strong>84.5%</strong></td>
<td><strong>12.5%</strong></td>
<td><strong>3.7%</strong></td>
<td><strong>83.8%</strong></td>
</tr>
<tr>
<td>1.50m</td>
<td>82.8%</td>
<td>12.5%</td>
<td>4.0%</td>
<td>83.6%</td>
</tr>
<tr>
<td>1.60m</td>
<td>81.8%</td>
<td>12.6%</td>
<td>3.2%</td>
<td>84.2%</td>
</tr>
<tr>
<td>1.70m</td>
<td>81.8%</td>
<td>12.6%</td>
<td>3.2%</td>
<td>84.2%</td>
</tr>
<tr>
<td>1.80m</td>
<td>81.3%</td>
<td>13.3%</td>
<td>3.5%</td>
<td>83.2%</td>
</tr>
<tr>
<td>1.90m</td>
<td>80.6%</td>
<td>13.1%</td>
<td>2.2%</td>
<td><strong>84.6%</strong></td>
</tr>
<tr>
<td>2.00m</td>
<td>79.9%</td>
<td>13.5%</td>
<td>2.2%</td>
<td>84.2%</td>
</tr>
</tbody>
</table>

84.5% * 83.8% ≈ 70%
Data Cleaning

Introduction
Methodology
Results
Conclusions
Data Cleaning

- Filter
- Planarity Check
- Sub-Planarity Check
- Outlier Removal
Filter

Rules:
• A segment needs to consist of at least 50 points
• A segment’s average intensity value needs to be below 100
• A segment’s average number of returns should be above 1.5
• A segment’s maximum height is 50m

Avg. Intensity: 1460
Avg. nr of returns: 1.3
Max height: 70m
Planarity Check

Random Sample Consensus (RANSAC)

![Graph showing 2D RANSAC (Pedregosa et Al., 2008)]
Planarity Check

Remove:

Distance < 100mm
Planarity Check

Do not remove

Distance > 100mm
Sub-Planarity Check

Low number of returns to identify planes within segments
Sub-Planarity Check
Outlier Removal

Density-Based Spatial Clustering of Applications with Noise (DBSCAN)

Estimated number of clusters: 3

DBSCAN (Pedregosa et Al., 2008)
Outlier Removal

Introduction

Methodology

Results

Conclusions
Modelling Parameters

Tree Top

Higher Periphery

Periphery

Lower Periphery

Crown Base

Tree Base, Ground Height
## Modelling

<table>
<thead>
<tr>
<th>Vertex</th>
<th>X</th>
<th>Y</th>
<th>Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>v0</td>
<td>$x = a$</td>
<td>$x = b$</td>
<td>$x = c$</td>
</tr>
<tr>
<td>v1</td>
<td>$x = a - r$</td>
<td>$x = b$</td>
<td>$x = c$</td>
</tr>
<tr>
<td>v2</td>
<td>$x = a - \cos(60) \times r$</td>
<td>$x = b + \sin(60) \times r$</td>
<td>$x = c$</td>
</tr>
<tr>
<td>v3</td>
<td>$x = a + \cos(60) \times r$</td>
<td>$x = b + \sin(60) \times r$</td>
<td>$x = c$</td>
</tr>
<tr>
<td>v4</td>
<td>$x = a + r$</td>
<td>$x = b$</td>
<td>$x = c$</td>
</tr>
<tr>
<td>v5</td>
<td>$x = a + \cos(60) \times r$</td>
<td>$x = b - \sin(60) \times r$</td>
<td>$x = c$</td>
</tr>
<tr>
<td>v6</td>
<td>$x = a - \cos(60) \times r$</td>
<td>$x = b - \sin(60) \times r$</td>
<td>$x = c$</td>
</tr>
</tbody>
</table>
Modelling

Convex Hull

Alpha Shape

Alpha shape (Eich et Al., 2008)
Modelling

Introduction
Methodology
Results
Conclusions

 LOD0  LOD1  LOD2  LOD3.0  LOD3.1
Type Classification

Feature 1

Feature 2

A  B  C  D

0  5  10  15

A  B  C  D
Type Classification

Genera

Average intensity

- Acer
- Aesculus
- Ailanthus
- Alnus
- Betula
- Carpinus
- Corylus
- Crataegus
- Fagus
- Fraxinus
- Gleditsia
- Liquidambar
- Malus
- Pinus
- Platanus
- Populus
- Prunus
- Quercus
- Robinia
- Tilia
- Ulmus
Type Classification

Clades

Average intensity

Average nr of returns

Angiospermae  Coniferae
Results

Good examples
Results

Remaining inaccuracies

Outliers

Under-segmentation

Misclassification
Results
Results
Results
Penetrating the irregular ground

Open Gap Penetration
Comparison

Reconstruction

(Verdie et al., 2008)
Comparison

(Du, 2019)
How can 3D tree models at varying Levels of Detail be automatically constructed from airborne LiDAR point cloud data?

- This implementation shows how
- 85% trees recognized
- 70% is modelled correctly
- Multiple LODs supported

How can a final implementation be made to fit into the 3dfier pipeline?

- For simple visualization, it fits
- For a seamless fit, more work needs to be done
Future Work

- Ground Truth for AHN3
- Post-Segmentation improvements
- Tree trunks
- Seamless integration 3dfier
Automatic construction of 3D tree models from airborne LiDAR data in multiple levels of detail

Geert Jan (Rob) de Groot
g.j.robdegroot@gmail.com

Supervisors:
Prof. dr. Jantien Stoter
Dr. Hugo Ledoux