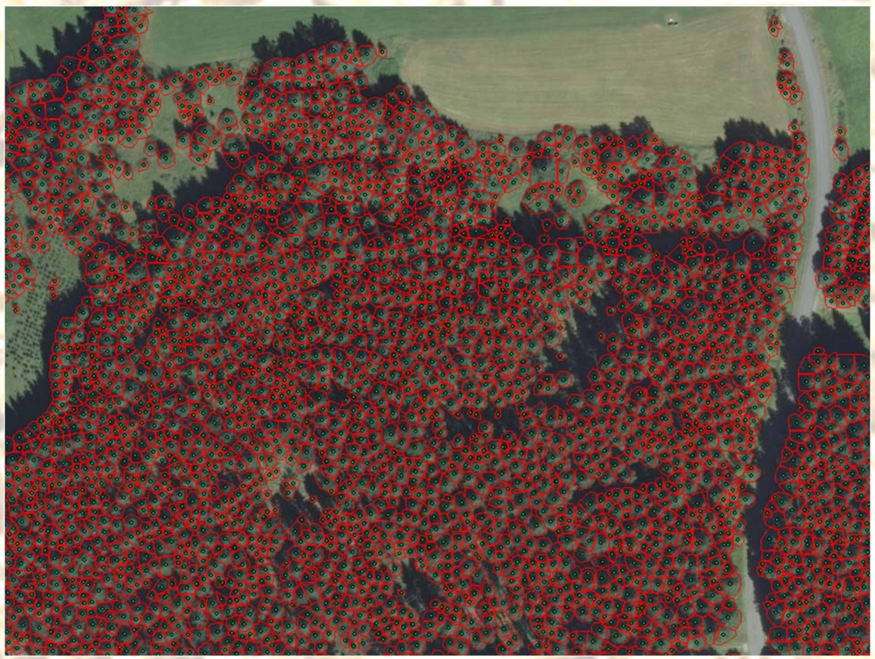

LiDAR-based 3D Mapping Of Forests

Photogrammetric Week

2017-09-14

Peter Krzystek

Przemyslaw Polewski

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Importance of forest structures

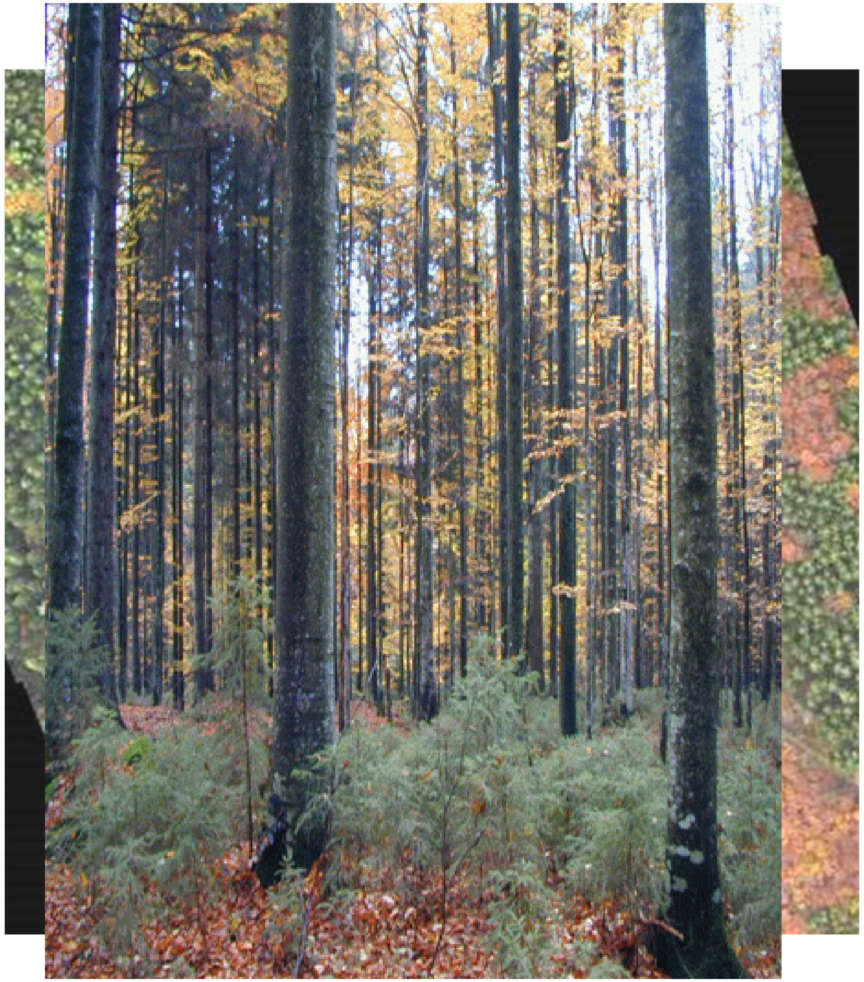


Image source: Bavarian Forest National Park

- Knowledge about forest structures is important
  - Basis for planning and management of natural resource
  - Evaluation of forest diversity
  - Basic information for forest research
- Conventional forest inventory
  - Subdivision of forest area into grid (e.g. 4km x 4km)
  - Sampling of forest in circular plots

Conventional forest inventory

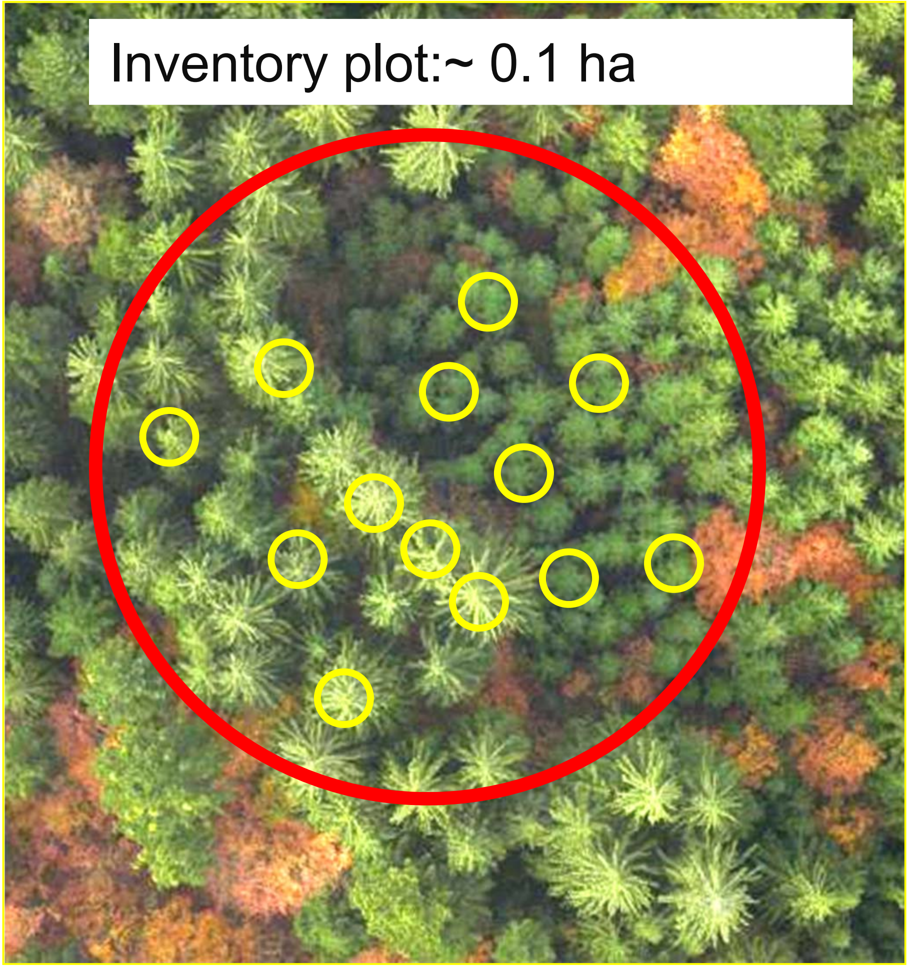


Image source: Bavarian Forest National Park

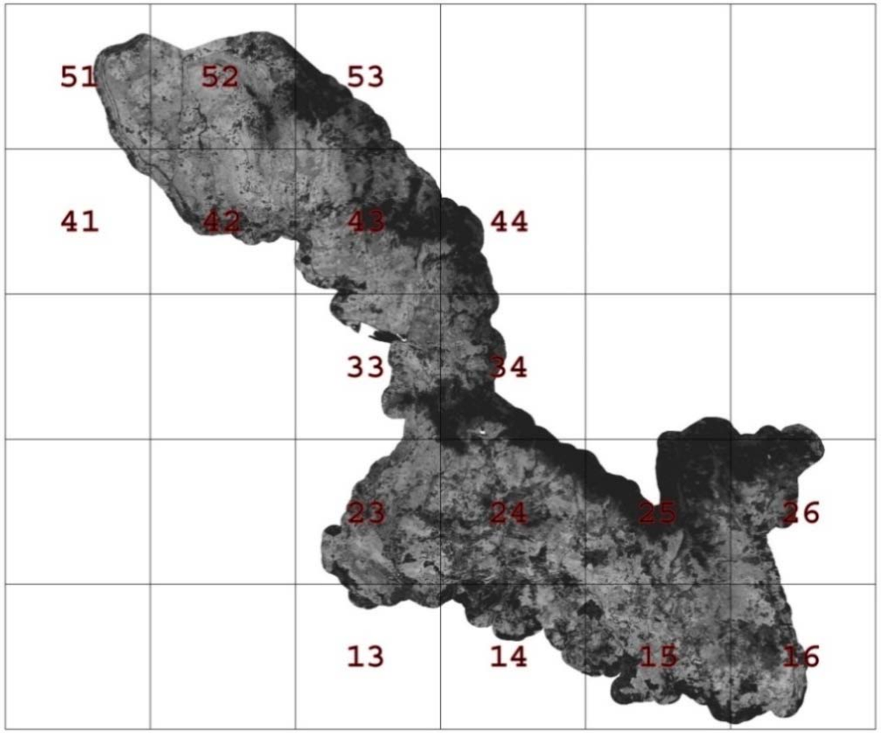
- Data acquisition in a sample circle for
  - Tree position
  - Tree height
  - Diameter at breast height (> 7 cm)
  - Crown base height
  - Tree species
  - Tree age
  - Regeneration
  - Dead wood
- Parameters of inventory
  - Percentage of tree species
  - Stock of wood and wood growth
  - Wood harvest

Outline

- Conventional vs. automated forest inventory
- Remote Sensing data sets
- Detection of single objects in forests
  - Single trees
  - Tree species classification
  - Standing dead trees
  - Falles dead trees with ALS
  - Fallen dead trees with TLS
- Conclusions

Remote Sensing Data

Size of forest area: ~ 300 km^2



Bavarian Forest National Park

- **ALS flight campaign**
  - Date: April 2011 (leaf-off)
  - Date: July 2012 (leaf-on)
  - Sensor: Riegl 680i (Full waveform)
  - Flying height: 650 m
  - Footprint size: 0.32 m
  - Point density: 30 - 40 pts/m^2
- **Aerial image flight campaign**
  - Date: August 2012
  - Camera: DMC
  - End lap: 80 % Side lap: 60 %
  - Flying height: 1900 m
  - GSD: 20 cm

Remote Sensing Data

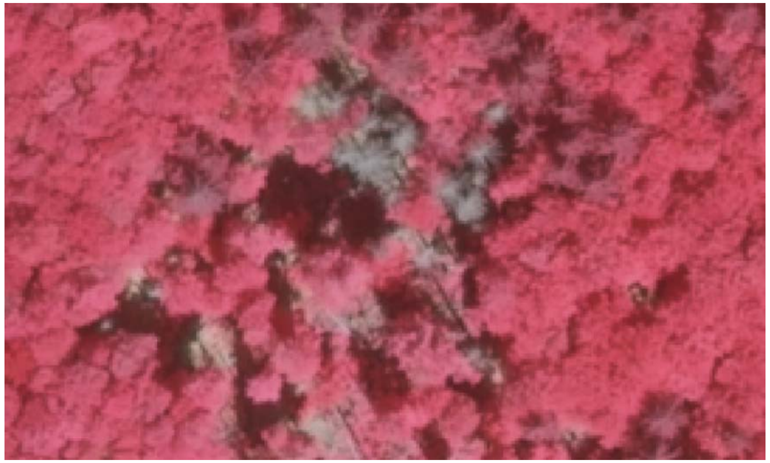


Image source: Bavarian Forest National Park

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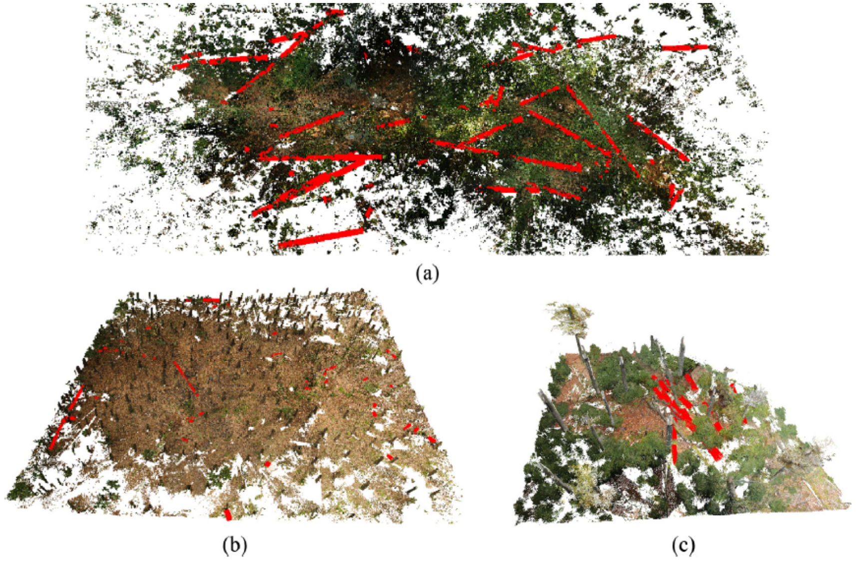
Remote Sensing Data

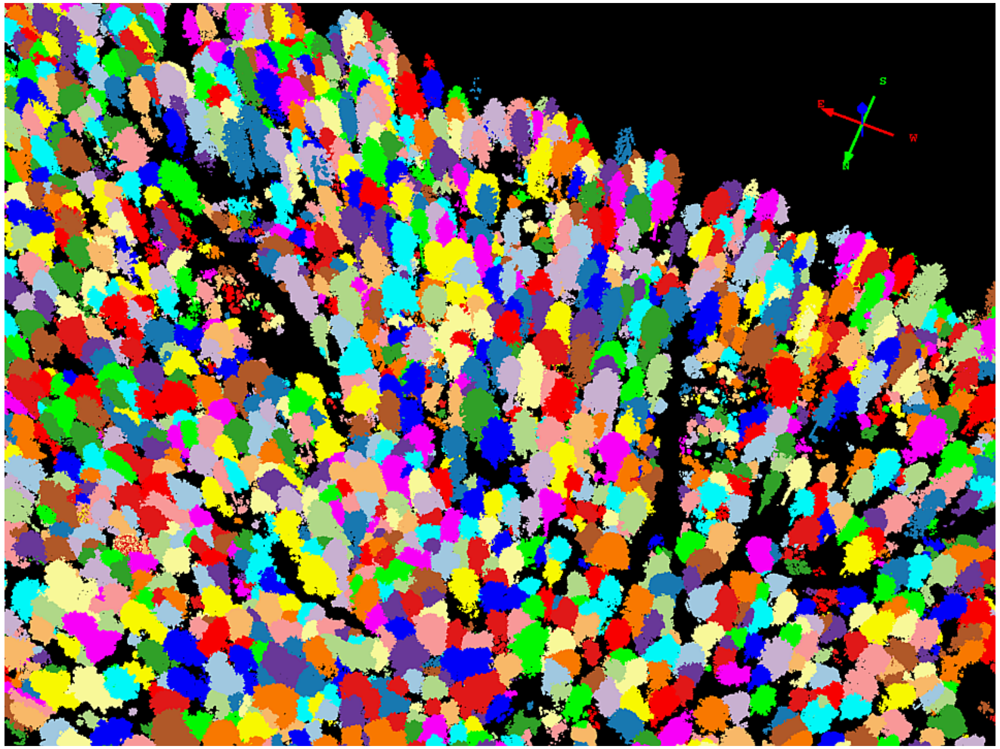


- **TLS data**
  - Date: June/August 2009 (leaf-on)
  - Date: October 2011 (leaf-on)
  - Sensor: Riegl LMS Z390

Property	Plot A	Plot B	Plot C
Num. fallen trees	61	47	29
Median stem diameter (cm)	47 ± 11	25 ± 3	27 ± 8
Median stem length (m)	3.2 ± 2.4	1.2 ± 0.4	1.5 ± 0.8
Median points per stem	1357	285	4047

Polewski et al., 2017b.

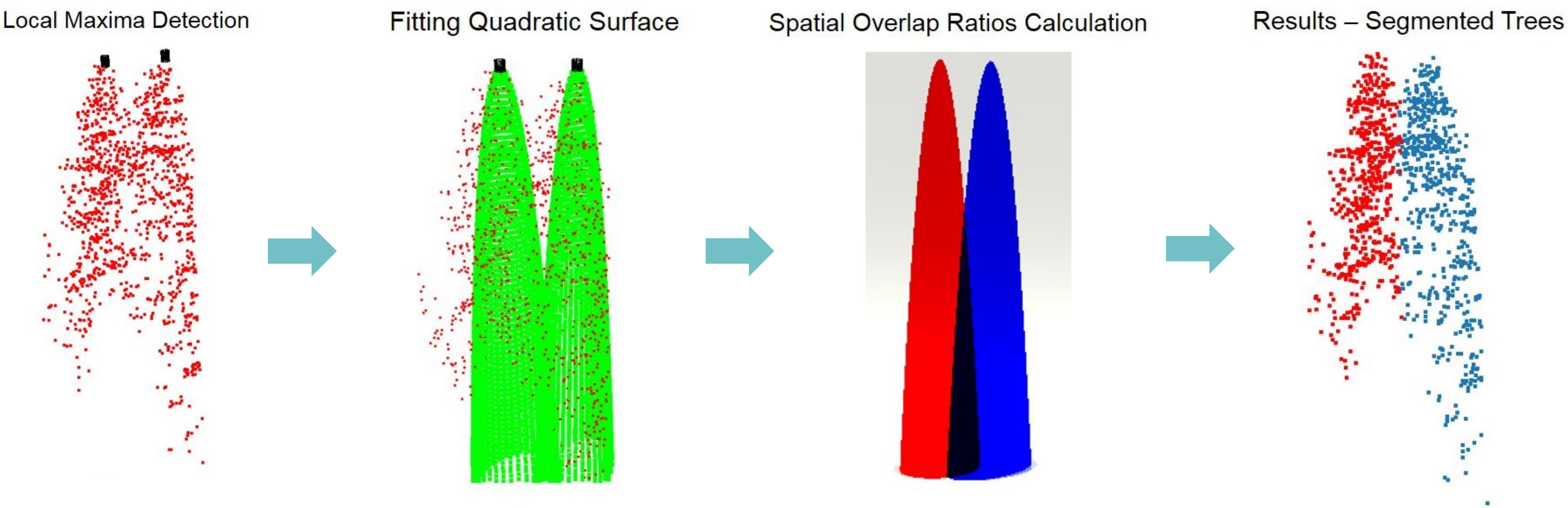
Single Tree Detection



- Graph-based algorithm for clustering data (Shi and Malik, 2000)
- Tends to find balanced partitions
  - Simultaneous maximization of within-cluster similarity and cross-cluster dissimilarity
- Wall-to-Wall solution
  - Fully automatic processing
  - Speed: 6 min/ha

Single Tree Detection

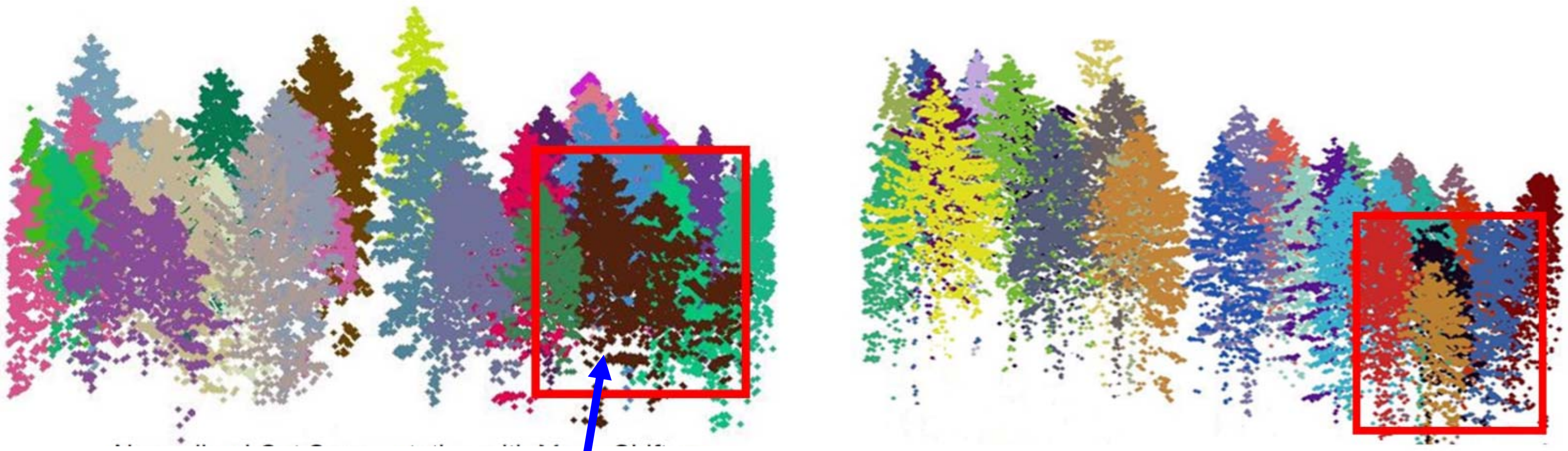
- Addaptive stopping criterion to avoid under/over segmentation
- Trained classidier decides if current segment contains more than one tree



Amiri et al., 2016b.

Single Tree Detection

Amiri et al., 2016b.



Undersegmentation

One segment (brown) contains two trees

Detection rate of single trees from LiDAR data

Height layer	LiDAR		
Lower (< 50 % Top_h)	51		
Middle (50% - 80% Top_h)	67		
Upper (> 80% Top_h)	75		

Comparison to watershed segmentation from DSM

- DSMs have been calculated from aerial imagery
- Three algorithms available to extract a DSM by dense matching (i.e. semi-global matching)
  - SGM: Original implementation (Hirschmüller, DLR)
  - MATCH-T: Software solution by Trimble
  - SURE: Modified SGM approach (IfP, Stuttgart University)

Detection rate of single trees from point clouds

Height layer	LiDAR	SURE	MATCH-T
Lower (< 50 % Top_h)	51	29	26
Middle (50% - 80% Top_h)	67	58	23
Upper (> 80% Top_h)	75	66	46

Single tree detection with LiDAR data performs best in the lower forest layer

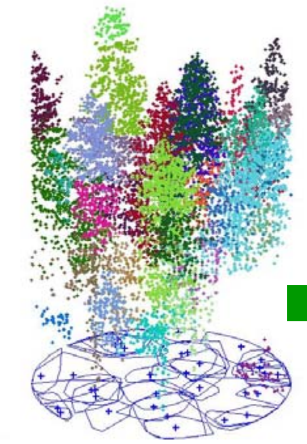
Outline

- Conventional vs. automated forest inventory
- Remote Sensing data sets
- Detection of single objects in forests
  - Single trees
  - Tree species classification
  - Standing dead trees
  - Fallen dead trees with ALS
  - Fallen dead trees with TLS
- Conclusions

Tree Species Classification

- Basis for forest management
- Contribution to forest biodiversity
- LiDAR-based classification of coniferous and deciduous trees with 95% accuracy is possible

Tree Species Classification



ALS features - 3D

- Geometric features
- Radiometric features
- *Bag-of-words model*

Multispectral aerial imagery features - 2D

- *Channel means and covariances*
- *Haralick texture features (GLCM)*
- *Gabor features*
- *Basic geometry features*

Feature selection
(Stepwise-forward)

Classification
(Logistic regression)

Amiri et al., 2016a.

Tree Species Classification

Feature sets	Average overall accuracy
Multispectral imagery - RGB	0.54
Multispectral imagery - Gabor	0.64
Multispectral imagery - GLCM	**0.68**
Multispectral imagery - RGB + Gabor + GLCM	0.67
ALS point clouds - Radiometric + Geometric	0.68
ALS point clouds - BoW (0.3-1.6m)	0.59
ALS point clouds - BoW (0.3-1.6m) + Radiometric + Geometric	**0.69**
Combined - GLCM + Radiometric + Geometric	0.71
Combined - GLCM + Gabor + BoW (0.3-1.6m) + Radiometric + Geometric	0.72
Combined - GLCM + BoW (0.3-1.6m) + Radiometric + Geometric	**0.73**

Amiri et al., 2016a.

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Dead tree detection - Motivation

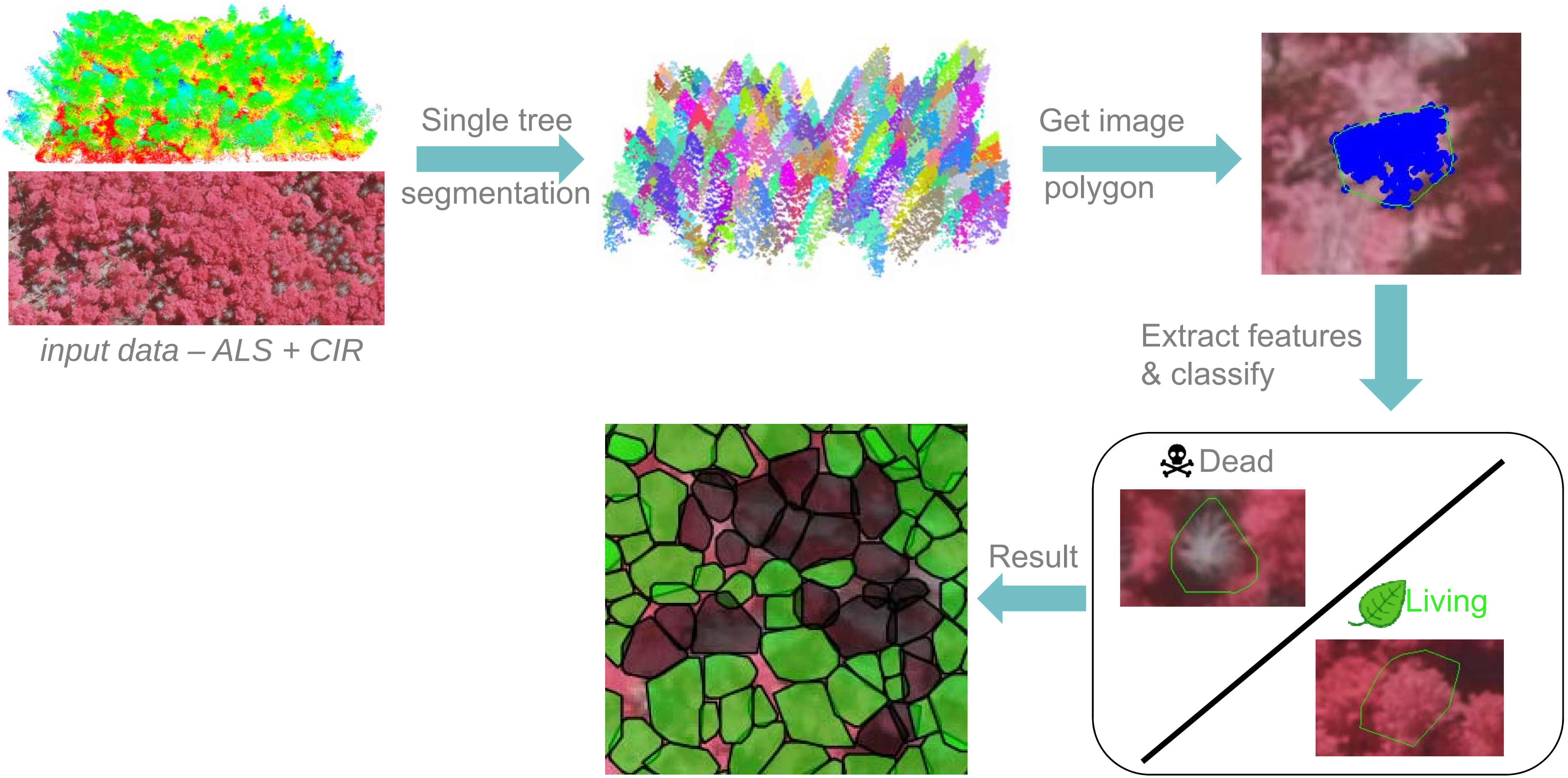
Image source: Bavarian Forest National Park

- Why is information about dead trees necessary?
  - Studying biodiversity and nutrient cycles in forests
  - Estimation of forest carbon stock
    - About 20% percentage of total carbon stocks in forests
    - Significant for greenhouse gases monitoring
  - National and international regulations regarding forest habitat monitoring

Dead tree detection - Goals

- We need methods capable of
  - Estimating the area-based coverage of dead trees
  - Estimating the total volume of dead trees
  - Calculating positions and characteristics of single dead trees
- The methods need to cope with difficult scenarios
  - Presence of near-by living trees
  - Complex spatial configurations of multiple overlapping stems
  - Presence of regeneration and/or vegetation
  - Presence of moderate overstory cover

Detection of standing dead trees (with crown)

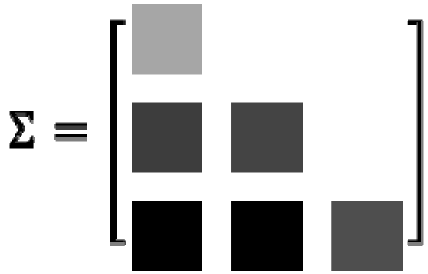


output – classified tree polygons

Polewski et al., 2016.

Detection of standing dead trees (with crown)

- Classification
  - Classifier: Logistic regression
  - Features
    - Mean values of green, red and IR band
    - Six independent elements of covariance matrix



  - Results
    - Number of labeled objects: 500
    - Class distribution: 8%
    - Overall accuracy: 90%

Polewski et al., 2016.

Detection of single dead trees (without crown)

- Tree trunks (=snags) have very small cross-section area
  - Difficult to classify when viewed from above
  - Using shadows as auxiliary information is inaccurate

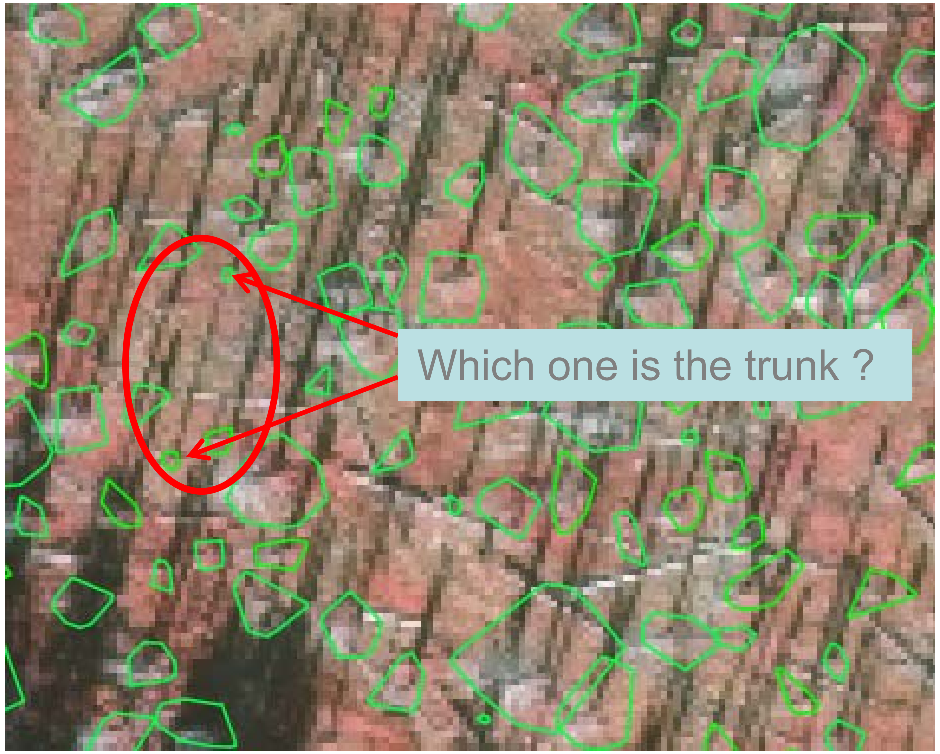
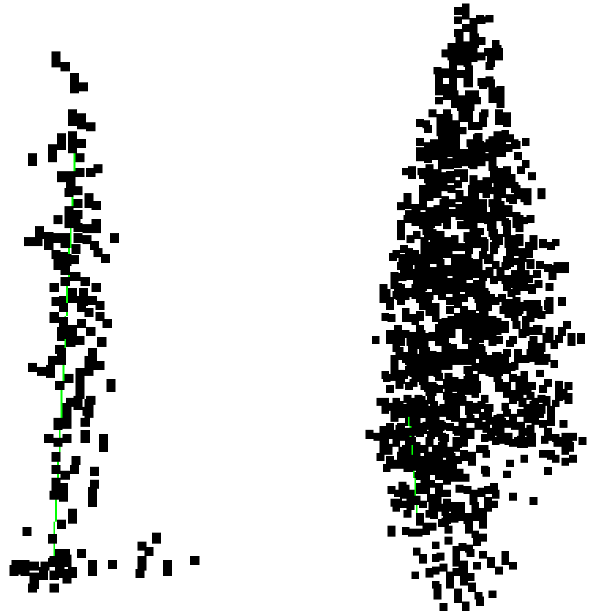
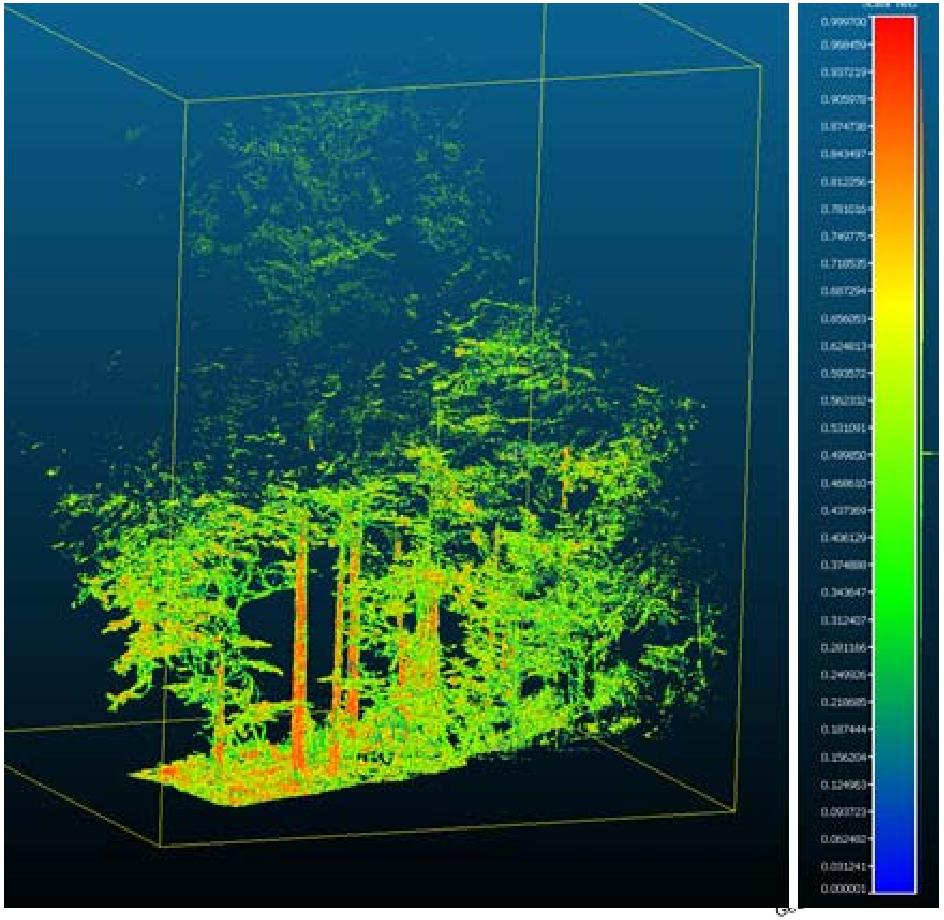


Image source: Bavarian Forest National Park

Solution: perform detection directly in 3D point clouds



Methods (Point classification)



Feature Linearity in a small forest scene

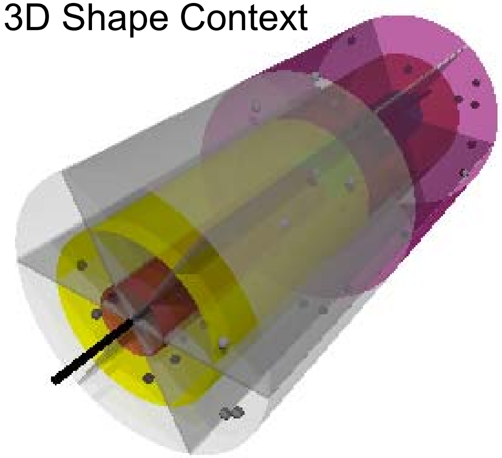
- Point Feature Histogramms
- Bag-of-Features based on Covariance Eigenvalues

Linearity:	$L_\lambda = \frac{e_1 - e_2}{e_1}$
Planarity:	$P_\lambda = \frac{e_2 - e_3}{e_1}$
Scattering:	$S_\lambda = \frac{e_3}{e_1}$
Omnivariance:	$O_\lambda = \sqrt[3]{e_1 \, e_2 \, e_3}$
Anisotropy:	$A_\lambda = \frac{e_1 - e_3}{e_1}$
Eigenentropy:	$E_\lambda = - \sum_{i=1}^{3} e_i \ln(e_i)$
Sum of eigenvalues:	$\Sigma_\lambda = e_1 + e_2 + e_3$
Change of curvature:	$C_\lambda = \frac{e_3}{e_1 + e_2 + e_3}$

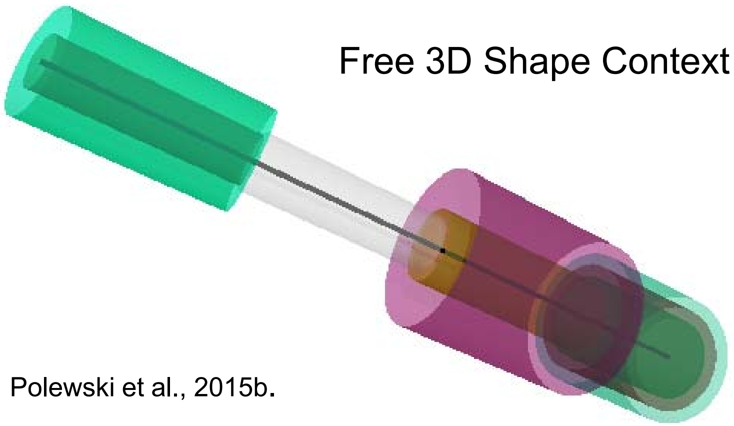
Weinmann et al. 2014, PCV

Methods (Classification of cylindrical segments)

3D Shape Context



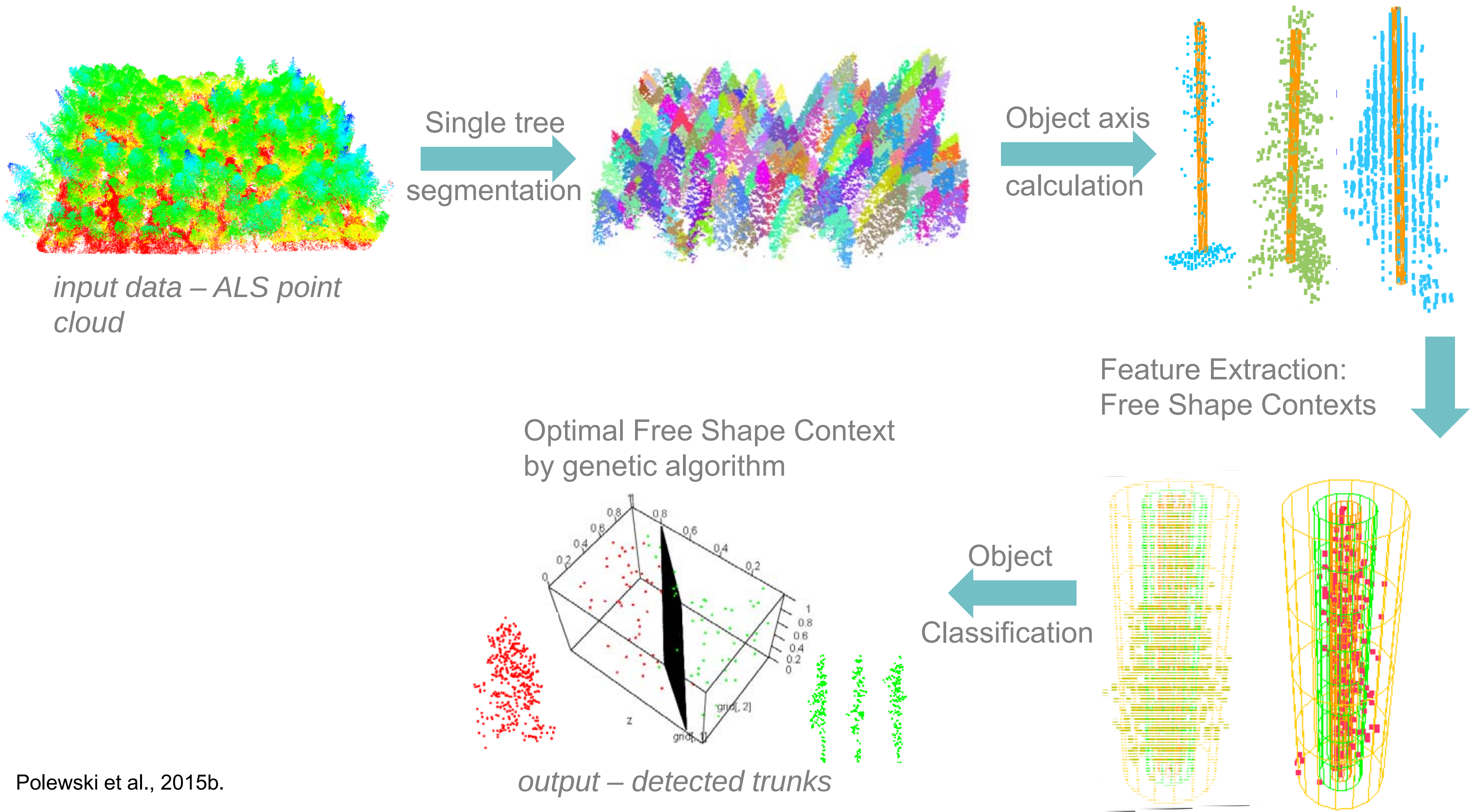
Free 3D Shape Context



Polewski et al., 2015b.

- Shape Descriptor from Computer Vision community
  - Originally spherical, describing neighborhood of one point
- Adapted to object level
  - Describes cylindrical neighborhood around main object axis
  - Subdivided in 3 dimensions: radial, axial and angular
- Features: normalized point counts in bins
- Free Shape Contexts
  - Stack of 3D Shape Contexts around common axis

Detection of single dead trees (without crown)



Polewski et al., 2015b.

Detection of single snags

- Classification
  - Classifier: Logistic regression
  - Features
    - Radius of minimal circle which encloses the projection of all points in the segment onto a plane
    - Number of points per segment
    - Length of axis found by MSAC (with tilt)
    - Free Shape Contexts
      - Normalized point counts in bins
  - Results
    - Number of labeled objects: 400
    - Class distribution: 8%
    - Overall accuracy: 88 %

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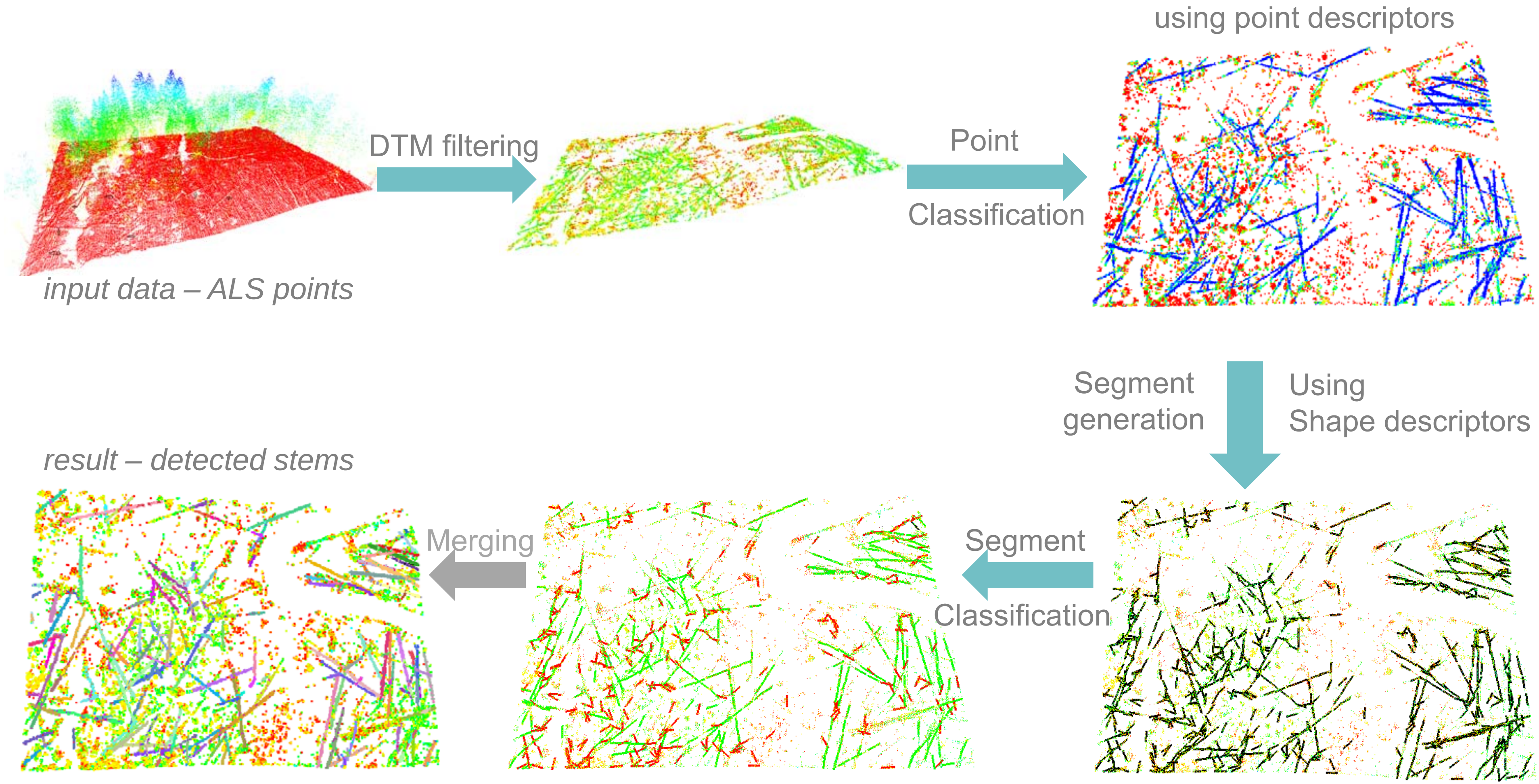
Detection of fallen dead trees

Aerial photo of an open forest area with downed tree

TLS colored point of an area with ground vegetation and downed trees

Image source: Nationalpark Bavarian Forest

Detection of fallen dead trees **Overview of method**



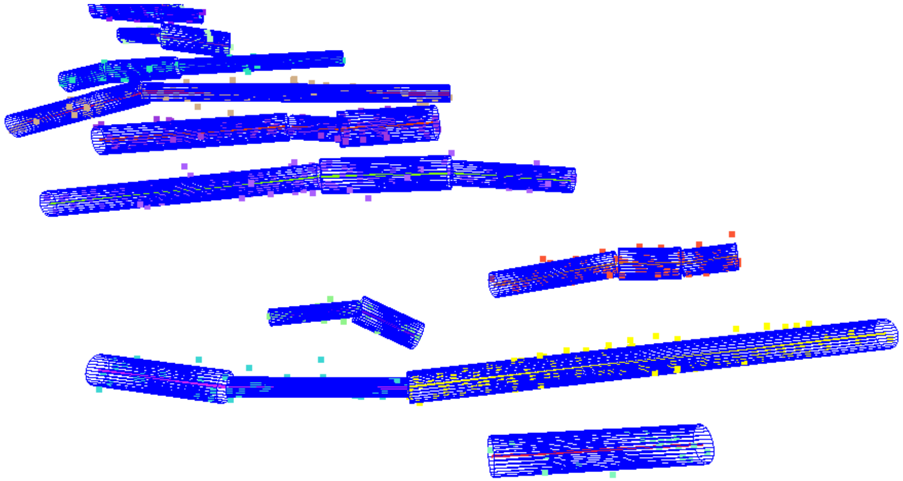
Polewski et al., 2015a; Polewski et al., 2017a

Detection of fallen dead trees

Merging of single tree segments by the Ncut segmentation

$$Ncut(A,B) = \frac{cut(A,B)}{assoc(A,V)} + \frac{cut(A,B)}{assoc(B,V)}$$

The Ncut segmentation is used as a classifier trained by simulated data



Simulate stem scenario by generating copies of prototypes at random locations and with random orientations.

Detection of fallen dead trees

- Reference data: field measurements of tree positioned
- Training data: two plots of ca 1 ha each
- Tested on 5 plots (LiDAR data are acquired in leaf-off situation!)
  - 3 dominated by deciduous species (Plot 1-3)
  - 2 dominated by coniferous species (Plot 4-5)

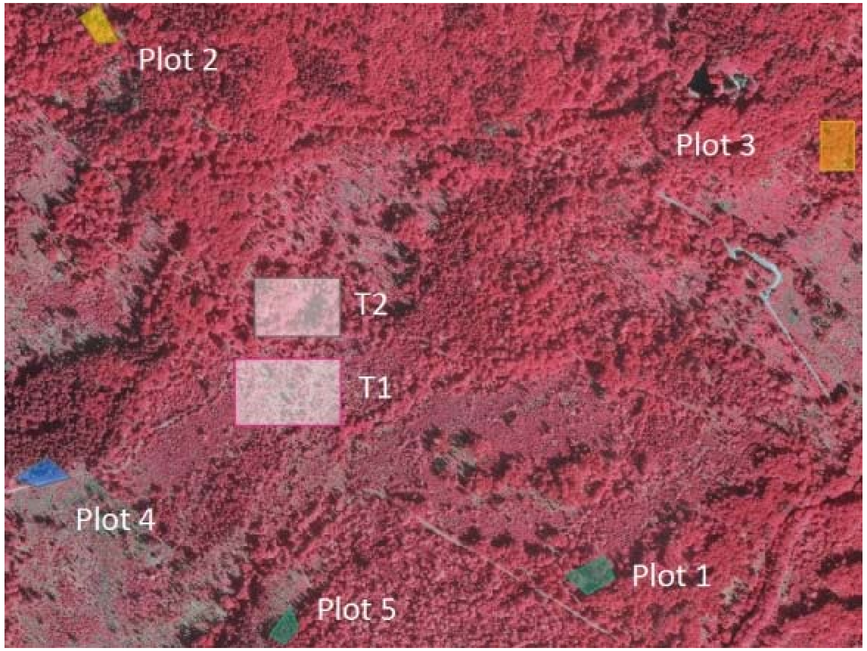


Image source: Bavarian Forest National Park

Detection of fallen dead trees

Plot#	Dominant species	Num. trees	Correctness	Completeness	Threshold
1	Beech	33	0,82	0,86	0,5
2	Beech	37	0,88	0,76	0,5
3	Beech	25	0,83	0,74	0,5
4	Spruce	35	0,92	0,51	0,3
5	Spruce	16	0,81	0,63	0,3

Polewski et al., 2015a; Polewski et al., 2017a

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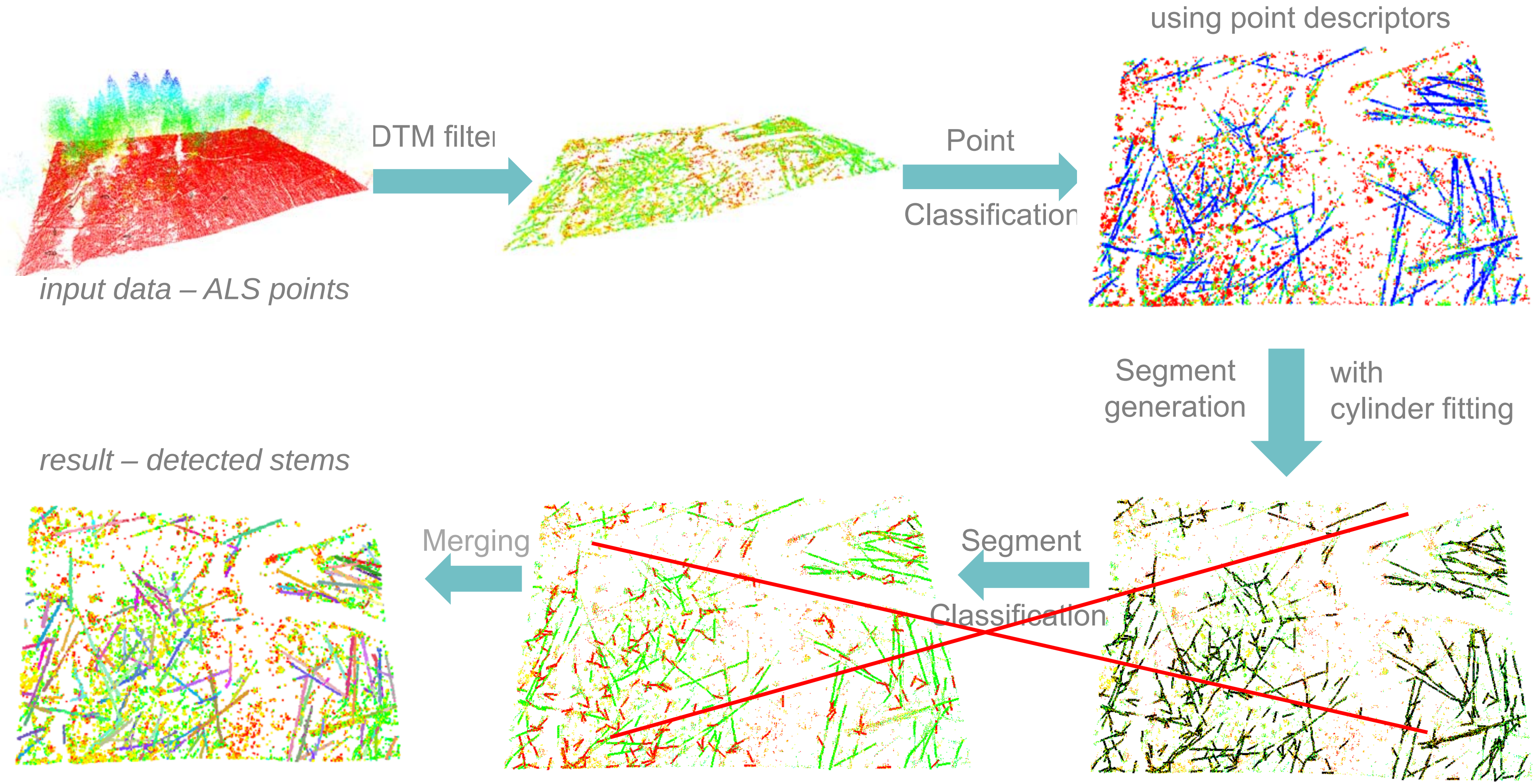
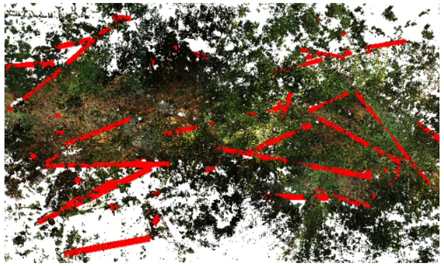
Detection of fallen dead trees (With TLS)

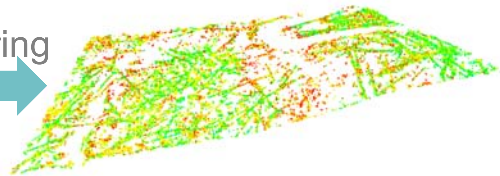


Detection of fallen dead trees (With TLS)



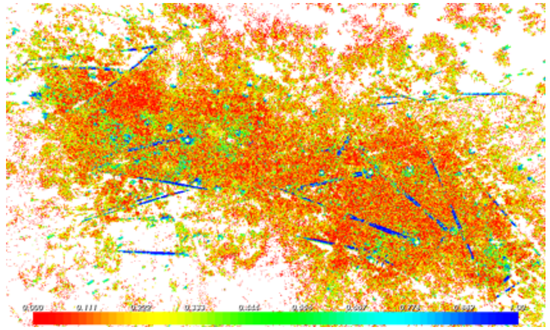
input data – ALS points

DTM filtering



Point Classification

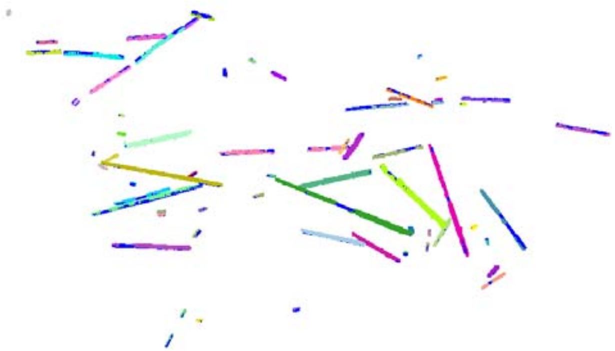
using point descriptors



Segment generation with cylinder fitting

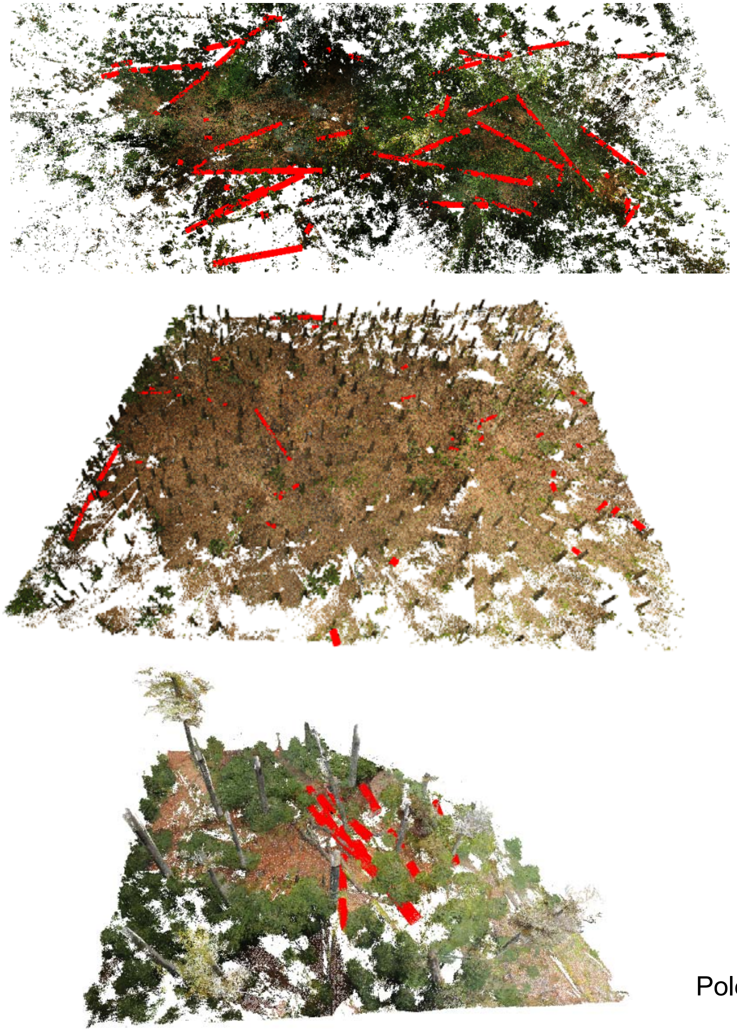
Merging

result – detected stems



Polewski et al., 2017b.

Detection of fallen dead trees (With TLS)



Data set	Correctness	Completeness
Plot A	82%	75%
Plot B	70%	52%
Plot C	83%	78%

Polewski et al., 2017b.

Conclusions

- Tools from machine learning and computer vision enable successful detection of forest objects (Single trees, dead wood)
- Accuracy mainly dependent on point density (> 20 pts per sqm)
  - Single trees: 80 % (Upper forest layer)
  - Dead wood
    - Standing dead trees: 90 %
    - Fallen dead trees: 80% (ALS and TLS)
- Large area mapping is feasible
- Tree species classification needs improvement

Outlook

- Tree species classification with MLS LiDAR data using three different wavelenghts

Literature

Amiri, N., Polewski, P., Yao, W., Heurich, M., Krzystek, P. and Skidmore, A.K., 2016a. Feature relevance assessment for single tree species classification using ALS point clouds and aerial imagery. In: Proceedings of the Young Professionals conference on remote sensing 2016, 20-21 October 2016, Overpfaffenhofen, Germany. 3 p.

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