

Automated Mapping Of Tree Crowns For Forest Inventory Using Remote Sensing Data Procesing The Defence Of The Thesis

Linda Gulbe, supervisor Dr. sc. comp. Ints Mednieks

University of Latvia

10.01.2020.

# 1. Practical tasks

- Mapping of tree crown coverage using satellite imagery, aerial images, Lidar data processing and interpretation of the results
- Localisation of individual trees and delineation of the tree crown contours using Lidar and multispectral data



Semantic segmentation of tree crown coverage

Instance segmentation of individual tree crowns

- to the reliability of the classification results of medium spatial resolution multispectral satellite images and to develop a user-friendly hybrid classification workflow
- to evaluate methods and algorithms for tree crown coverage segmentation (classification) using very high spatial resolution data
- to study and to develop solutions for localization and delineation of individual tree crowns using Lidar and multispectral data

# 3. Study sites



Reference data:

- A1 crown centres, tree species and crown contours for 270 trees
- A2 1124 training points, 1000 test points for land cover classes
- A3 2601 training points, 1549 test points for land cover classes

# 3. Study sites



Figure: Study site A3. Red points - training data, blue points - test data

### 4. Remote sensing data

- A1: Lidar ( 4*pts/m*<sup>2</sup>), multispectral aerial images (0.5 m/pix, 13 bands in visible and near infrared range) obtained by Institute of Environment Solutions in 13.05.2008.
- A2 and A3: Lidar (> 4pts/m<sup>2</sup>), CIR orthophotomaps (0.4 m/pix, 0.25 m/pix) provided by Latvian Geospatial Information Agency, Landsat satellite images (30 m/pix), Sentinel-2A,2B satellite images (10-20 m/pix)



Improvements of the methods and the developed methods for the tree crown coverage mapping during the doctoral studies:

- Developed hybrid classification work-flow for medium spatial resolution multispectral satellite images and low quality training data
- Performed case studies to answer the research questions

Research questions:

- How are the results of the classification affected by the unique conditions at the time of image acquisition?
- What are the relationships between the spectral classes and forest inventory parameters?
- What is the compatibility of the classification results from different seasons?
- What are the common causes of tree crown mapping errors?
- Does the application of convolutional neural networks by using high spatial resolution data provide higher accuracy than simpler workflows?

# 5.1. Hybrid classification workflow



# 5.2. How are the results of the classification affected by the unique conditions? (A2)

Image	OA (%)	PA (%)	UA (%)	ĥ
		TC/O	TC/O	
LC81870202014023LGN00	94.2	98.7/90.5	90.0/98.8	0.89
LC81870202014055LGN00	91.2	95.5/87.5	86.9/95.7	0.82
LC81870202014087LGN00	93.6	97.8/90.0	89.6/98.0	0.87
LC81870202014135LGN00	83.7	98.9/70.5	74.4/98.7	0.68
LC81870202014215LGN00	86.2	98.9/75.1	77.6/98.8	0.73
LC81870202014247LGN00	88.4	98.9/79.2	80.6/98.8	0.77
LC81870202014263LGN00	92.8	98.2/88.1	88.0/98.2	0.86
LC81870202015074LGN00	86.6	99.6/75.3	77.8/99.5	0.74
LC81870202015186LGN00	86.0	98.5/75.0	77.6/98.3	0.72
S20150824T094301	91.1	89.7/92.3	91.0/91.1	0.82
S20170316T094021	89.3	85.0/93.1	91.4/87.7	0.78

# 5.3. What are the relationships between the spectral classes and forest inventory parameters? (A2)

Sp. class	Area ( <i>km</i> <sup>2</sup> )	Land cover class (hybrid workflow)	Average tree cover (%)	Notes
1	47	0	31.9	Non-homogeneous class
2	65	ТС	57.5	New stands, sunlit side of stands
3	211	ТС	91.2	
4	32	тс	67.8	Shadowed side of the stand
5	108	ТС	94.6	
6	36	0	20.2	
7	34	0	10.0	
8	20	0	5.9	

Table: Image LC81870202014023LGN00

# 5.4. What is the compatibility of the classification results from different seasons?



Figure: First row - tree cover in january, april and july. Second row - changes in tree cover classification results. Gray - no changes, white and black - changes

# 5.5. What are the common causes of tree crown mapping errors?



Figure: Red dots - test points where other land cover type is classified as forest

Dati	OA (%)	PA (%) for-	UA (%) for-	ĥ
		est/other	est/other	
Sentinel 28.05.2017.,	73.5	77.7/68.4	75.5/71.0	0.46
kNN				
Sentinel 28.05.2017.,	84.18	90.2/76.6	82.8/86.3	0.68
hybrid				
Thresholding	92.8	91.9/93.9	95.0/90.2	0.85
U-Net, nDSM	91.3	96.3/85.1	88.8/94.9	0.82
U-Net, CIR+nDSM	91.2	85.7/97.9	98.1/84.8	0.82
Hansen et al.	83.5	88.9/76.7	82.7/84.8	0.66
EC's JRC Pan-	83.7	87.9/78.5	83.6/83.8	0.66
European Forest/Non				
- Forest Map 2000.				
CORINE 2012	83.7 (83.1)	86.6/79.9	84.4/82.7	0.67 (0.66)
		(84.9/80.8)	(84.7/81.0)	

Table: A3: accuracy assessment

Improvements of the methods and the developed methods for the tree crown coverage mapping during the doctoral studies:

- Improvements for the template matching method: 1) implementation of data fusion of multispectral and Lidar data, 2) response filtering and resizing of the template
- ② Developed new method EATG for optimal template set preparation
- Developed decision based method for tree crown delineation by using data fusion
- Convolutional neural network Mask RCNN was evaluated

# 6.1. Template Matching (TM)

1. Template is "slided over" the aerial image

2. For every pixel location normalized correlation coefficient is calculated

3. Correlation coefficient image is thresholded using threshold value T







4. Pixel with the highest correlation coefficient value within each connected component becomes a tree crown point



Within the framework of the thesis, TM was improved by adding:

- The D<sub>min</sub> parameter determines the closest possible distance between two tree tops
- The *TE<sub>size</sub>* parameter allows to resize the template during the TM process using image resizing
- Processing of multiband images (including multisource data)
- Template Generation using training data and ideas of evolutionary algorithms

Template size	Trees	Omitted	False	Accuracy
change (%)	found $N_p$	trees $N_o$	positives	Index
	(gab.)		N <sub>c</sub>	(AI) %
Without change	152	125	19	48.0
75:100	205	72	53	54.8
50:75:100	177	100	96	34.7
100:125	155	122	25	46.9
100:150	156	121	22	48.4
75:100:150	200	77	53	53.1

Table: A1, NIR image. 277 trees in study site

Image	Trees	Omitted	False	Accuracy
	found N <sub>p</sub>	trees N <sub>o</sub>	positives	Index
	(gab.)		N <sub>c</sub>	( <i>AI</i> ) %
NIR	205	72	53	54.8
nDSM	152	125	104	26.7
Fused NIR &	178	99	91	31.4
nDSM				
NIR + nDSM (2	225	52	50	63.2
bands)				

Table: A1, 277 trees in study site

The idea of (1 + 1) EA was extended to the template generation task:

- Generate the 1st template V by using a 2D Gaussian distribution function and by adding a Gaussian noise to it
- Generate Offspring P by adding a recalculated Gaussian noise to the V
- Run the TM procedure on both templates and find the best of the V and P according to the accuracy index
- The best template becomes the new Parent V and steps 2 through 4 are repeated until the stop criterion is reached

# 6.2. EATG for template preparation











Data set	Al 1st	N <sub>c</sub>	No	Al 5 tem-	N <sub>c</sub> 5	<i>N</i> <sub>o</sub> 5
	template	1st t.	1st t.	plates	t.	t.
NIR	49.46	9	131	54.87	21	104
nDSM	34.3	5	177	38.99	19	150
NIR+nDSM	24	3	205	29.2	3	193
(2 bands)						

Table: Stop criteria - 250 iterations without changing V for 1 band image, 600 iterations without changing V for 2 band image

1. Move tree top location point to a local maximum



- 2. Find the pixel values in 16 directions from the tree top location
- 3. Analysis of the pixel values to find the tree crown contour points



(x-1-1,y-1-1)	(x-1,y-1-1)	(x,y-1-1)	(x+1,y-1-1)	(x+1+1,y-1-1)	
(x-1-1,y-1)	(x-1,y-1)	(x,y-1)	(x+1,y-1)	(x+1+1,y-1)	
(x-1-1,y)	(x-1,y)	(x,y)	(x+1,y)	(x+1+1,y)	
(x-1-1,y+1)	(x-1,y+1)	(x,y+1)	(x+1,y+1)	(x+1+1,y+1)	
(x-1-1,y+1+1)	(x-1,y+1+1)	(x,y+1+1)	(x+1,y+1+1)	(x+1+1,y+1+1)	

4. Contour point adjustments for one data source



#### 5. Contour point averaging using multiple data sources



Figure: Red dots show the contour points after the averaging. Dots in green were found by using nDSM, pink by tree species clustering image No.1, dark blue by tree crown coverage mask, light blue by tree species clustering image No.2.

6. Building a polygon of a tree crown and formatting the results





(d)

(e)

### 6.4. Mask RCNN results



(d)

# 6.5. Accuracy of tree crown delineation

Overlap	o <sub>ref,i</sub>	o <sub>m,i</sub>	o <sub>ref,i</sub> deci-	o <sub>m,i</sub> decision
class	Mask	Mask	sion based	based work-
	R-	R-	workflow	flow +refer-
	CNN	CNN	+refer-	ence tree lo-
	+	+	ence tree	cations
	NIR	NIR	locations	
1%-19%	42	38	9	3
20%-39%	40	16	20	28
40%-59%	44	23	59	61
60%-79%	59	73	87	79
80%-100%	65	100	102	106
E <sub>A</sub>	11.29	-	11.9	-
Number of	250	250	277	277
tree crowns				

- Locally adjusted tree crown mapping solutions provide approximately 10% higher accuracy than publicly available global tree crown coverage maps
- The level of confidence describes the unambiguity with which a pixel or a spectral class is assigned to a land cover class and provides a valuable opportunity to evaluate the reliability of a thematic map at the level of each individual element to be processed
- The EATG generates the templates by using only the training dataset, without any input about the unique conditions at the time of image acquisition, grayscale values in the image, forest structure etc.
- The decision-based method is very flexible: no training data is required and the user can input arbitrary number of images

- Efficient use of a national aerodata database requires solutions for correcting nonsystematic geometrical misalignment
- There is a necessity for reference data set for Latvia including land cover data and tree crown contours for testing locally adjusted methods.
- Convolutional neural networks for tree crown delineation has to be studied in more details because further improvements are possible

# 9. Publications

- L. Gulbe, A. Kozlovs, J. Donis, A. Traškovs "Tree cover mapping using hybrid fuzzy c-means and Landsat satellite images", Baltic Forestry, 25(1), 113-123, 2019. Autores aptuvenais ieguldījums procentos: 80%. Indeksēts SCOPUS.
- M. Lang, L. Gulbe, A. Traškovs, A. Stepčenko "Assessment of different estimation algorithms and remote sensing data sources for regional level wood volume mapping in hemiboreal mixed forests", Baltic Forestry, 22 (2), 283-296, 2016. Autores aptuvenais ieguldījums procentos: 20%. Indeksēts SCOPUS.
- L. Gulbe "Identification and delineation of individual tree crowns using Lidar and multispectral data fusion", Geoscience and Remote Sensing Symposium (IGARSS), IEEE, 2015. Autores aptuvenais ieguldījums procentos: 100%. *Indeksēts SCOPUS*.

- L. Gulbe, G. Hilkevica "Vegetation Change Detection In Landsat TM Time Series Using Singular Spectrum Analysis and Regular Forest Inventory Data". 14th International Multidisciplinary Scientific GeoConference: GEOINFORMATICS AND REMOTE SENSING. Conference Proceedings. VOLUME: 3, p. 397-404. Section: Photogrammetry and Remote Sensing, 2014. Autores aptuvenais ieguldījums procentos: 80%. Indeksēts SCOPUS.
- L. Gulbe, I. Mednieks "Automatic Identification of Individual Tree Crowns in Mixed Forests Using Fusion of LIDAR and Multispectral Data", Scientific Journal of Riga Technical University. Technologies of Computer Control, Volume 14: 93-99, 2013. Autores aptuvenais ieguldījums procentos: 80%.