

Tree Defect Segmentation using Geometric Features and U-net

Florian Delconte¹; Phuc Ngo¹; Isabelle Debled-Rennesson¹; Bertrand Kerautret ²; Van-Tho Nguyen³ and Thierry Constant ⁴

RRPR 2021

Milano, 11 January 2021

¹LORIA, Nancy, France

²LIRIS, Lyon, France

³CARTEL, Sherbrooke, Canada

⁴INRAE, Nancy, France



INRAE



LIRIS

Cartel
Centre d'applications et de
recherches en télédétection

1. Context
2. State of the art
3. Segmentation process
4. Experimental results
5. Conclusion

1. Context

Forest production trading

Estimate the tree quality :

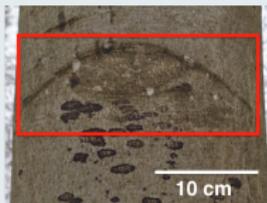
- Look at external defects
- Deduce the internal impacts

WoodSeer project : Evaluate the use of machine learning to predict the interior distribution of defects inside roundwood **from the external geometry of the wood.**

Defects diversity



Tree climbing



Branch scar (beech)



Branch scar (beech)



Picot (oak)

1. Context



TLS



Point cloud



Mesh



Defect detection

Approach

- Build a 2D representation of the trunk mesh
- Generate the training dataset
- Train a defects segmentation model
- Detect defects for new input data

2. State of the art

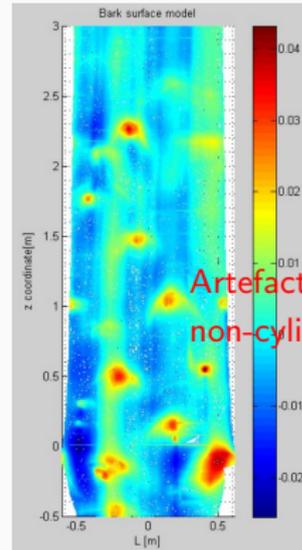
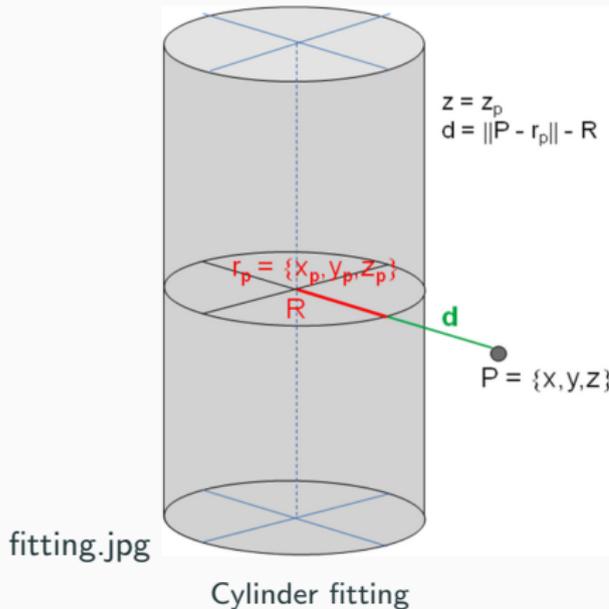
Main idea of the article

[KKM⁺13](2013) : build an intensity map by fitting a cylinder on the tree trunk point cloud, and then use it to detect trunk defects.

2. State of the art

Main idea of the article

[KKM⁺13](2013) : build an intensity map by fitting a cylinder on the tree trunk point cloud, and then use it to detect trunk defects.



Intensity map

2. State of the art

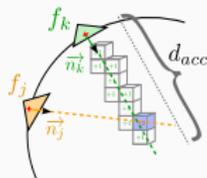
Main idea of the article

[NKDR⁺16](2016) : use the trunk centerline [KKDRL16] to segment defect via a local relief representation (called **delta distance**).

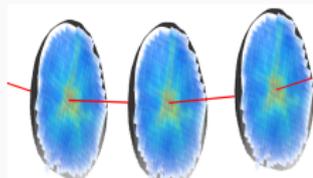
2. State of the art

Main idea of the article

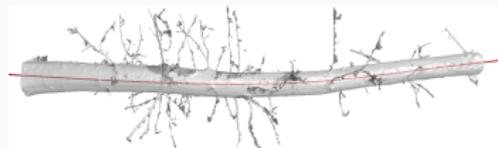
[NKDR⁺16](2016) : use the trunk centerline [KKDRL16] to segment defect via a local relief representation (called **delta distance**).



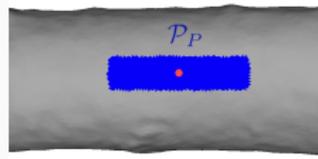
Accumulation



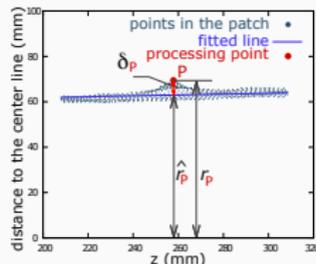
Tracking step



Centerline (red)



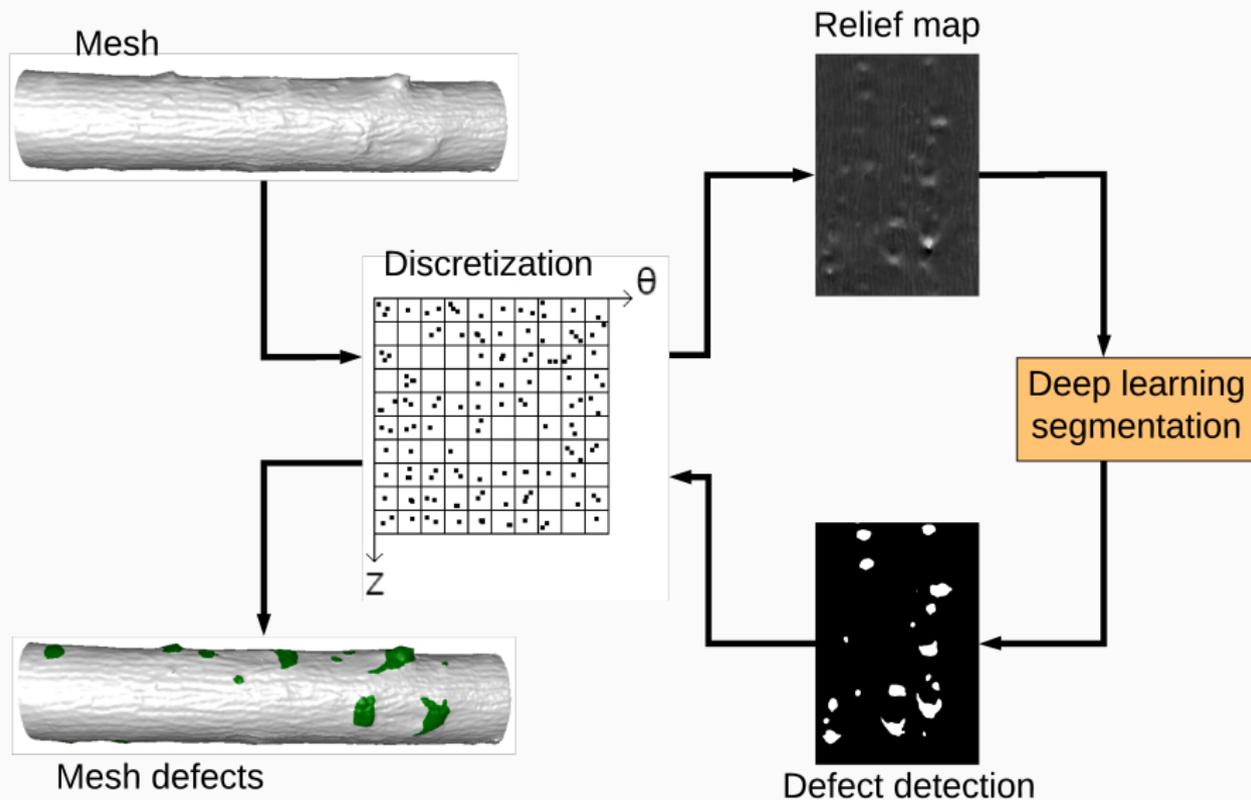
Patch



Delta distance

An automatic thresholding is used to classify the points as defects

3. Segmentation process



3.1 Relief map

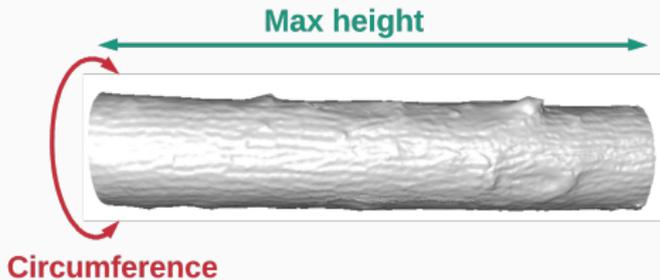
Discretisation

Width = $2\pi * r_m$, with r_m the average radius of the trunk.

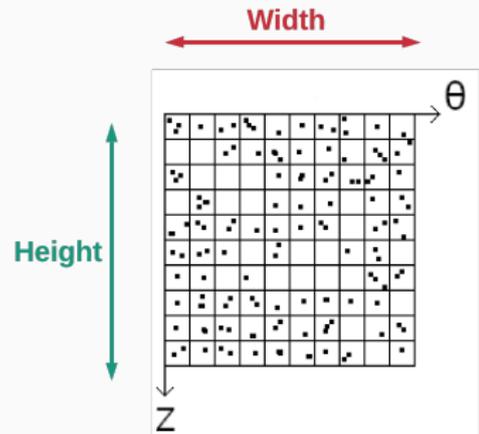
Height = $P_{z_{max}} - P_{z_{min}}$, with $P_{z_{max}}$ and $P_{z_{min}}$ are height max and min, respectively.

Value of the cells = maximum **delta distance** of all points in the cells.

Empty cells are recovered by a **multi resolution analysis**.



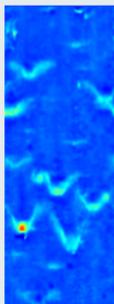
Mesh



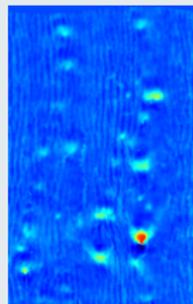
Discretization

3.1 Relief map

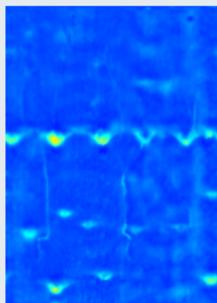
Examples of relief map (RGB)



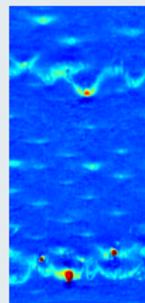
Birch



Elm



Fir

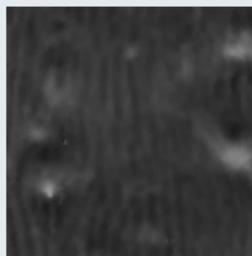


WildCherry

3.2 Segmentation with U-Net Architecture

Network training

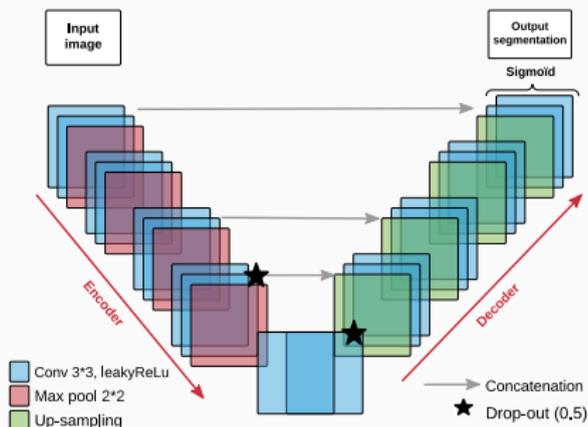
- U-Net [RFB15]: Auto encoder.
- Data : 25 relief maps cut out in 465 thumbnail.
- Parameters : 40 epochs, 63 steps, 10 images per batch (14s/epoch).



Relief map



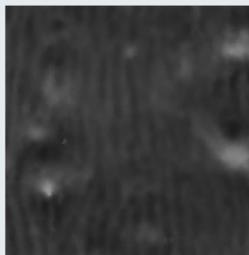
Label image



3.2 Segmentation with U-Net Architecture

Network training

- **U-Net** [RFB15]: Auto encoder.
- **Data** : 25 relief maps cut out in 465 thumbnail.
- **Parameters** : 40 epochs, 63 steps, 10 images per batch (14s/epoch).



Relief map



Label image

Details

- **GPU** : RTX 2080Ti with Tensorflow 2.2 and Keras.
- **Ground-truth** : Binary image (same dimension as the relief map).
- **Data augmentation** : Rotation, vertical and horizontal flip, zoom and deletion of rectangular area randomly [DT17].
- **Loss function** : Binary crossentropy.
- **Thumbnail size** : 320*320pi.

3.2. Segmentation with U-Net Architecture

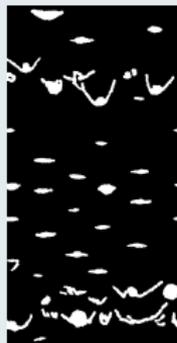
Test the prediction



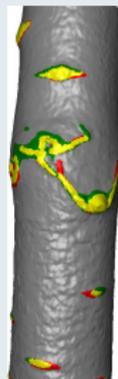
Input



Prediction



Ground truth



Mesh

Compared to the ground-truth

- Yellow is true positive.
- Red is false negative.
- green is false positive.

Details

- Prediction threshold = 0.5 for the normalized probabilities output
- Re-projection of the predicted defect output back to 3D point cloud

4. Results and reproducibility

Results

Dataset : 25 trunk samples with defect annotation.

F-measure (F1) : Harmonic mean of precision and recall.

Experiment 1 : Comparison with the rectangular patch method (15 samples for training and 10 for testing).

Our method (F1)	0.79
[NKDR ⁺ 16] Patch method (F1)	0.71

Experiment 2 : Robustness of the method over the dataset (5-fold cross-validation)

	K1	K2	K3	K4	K5
Our method (F1)	0.750	0.712	0.724	0.787	0.721
[NKDR ⁺ 16] Patch method (F1)	0.563	0.643	0.635	0.676	0.597

4. Results and reproducibility

Reproducibility

- Code, data and commands to reproduce results are available :
<https://github.com/FlorianDelconte/TLDDC>
- Free online demo (no need to install dependencies) :
<https://kerautret.github.io/TLDDC>



A screenshot of a web browser displaying the TLDDC online demo. The browser address bar shows the URL: https://kerautret.github.io/TLDDC. The page content includes a description of the tool as an 'Online demonstration of the RRPR 2020 submitted paper: Tree Defect Segmentation using Geometric Features and CNN'. It lists the authors: Florian Delconte, Phuc Ngo, Isabelle Delfino-Renaudon, Bernard Renaudon, Van-Tho Nguyen and Thierry Condamine. Below this, it states 'The source code can be found on this github : here' and provides a 'Select input()' dropdown menu with a 'Submit' button. The dropdown menu is open, showing seven tree species options: Aspen2, WhiteCherry2, Fir1, Birch, Beech, Aspen1, and Alder4. Each option is accompanied by a small thumbnail image of a tree. Below the species selection, there is an 'Input(s)' section and a 'Parameters' section. The 'Parameters' section has a 'Reset' button and three sliders: 'predictive threshold' (set to 1.75), 'geometric pad' (set to 100), and 'geometric origin' (set to 50). A 'Run' button is located at the bottom right of the parameters section. At the very bottom of the page, there is a small footer with a Creative Commons license and a link to the RRPR 2020 paper.

5. Conclusion

Contributions :

- A deep learning based approach to segment defects on meshes of tree trunks.
- Only 25 annotated trunk meshes are used.
- Bash script to reproduce the obtained results.
- An online demonstration.

Future works :

- Compare the performances of CNN architectures for the defect segmentation.
- Train a network for semantic segmentation (One color for each defect type).

References

-  Terrance Devries and Graham W. Taylor, *Improved regularization of convolutional neural networks with cutout*, CoRR **abs/1708.04552** (2017).
-  Bertrand Kerautret, Adrien Krähenbühl, Isabelle Debled-Rennesson, and Jacques-Olivier Lachaud, *On the implementation of centerline extraction based on confidence vote in accumulation map*, International Workshop on Reproducible Research in Pattern Recognition, Springer, 2016, pp. 116–130.
-  Ursula Kretschmer, Nadeschda Kirchner, Christopher Morhart, Heinrich Spiecker, et al., *A new approach to assessing tree stem quality characteristics using terrestrial laser scans*, *Silva Fenn* **47** (2013), no. 5, 1071.
-  Van-Tho Nguyen, Bertrand Kerautret, Isabelle Debled-Rennesson, Francis Colin, Alexandre Piboule, and Thiéry Constant, *Segmentation of defects on log surface from terrestrial lidar data*, 2016 23rd International Conference on Pattern Recognition (ICPR), IEEE, 2016, pp. 3168–3173.
-  Olaf Ronneberger, Philipp Fischer, and Thomas Brox, *U-net: Convolutional networks for biomedical image segmentation*, CoRR **abs/1505.04597** (2015).