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CNN-based Method for Segmenting Tree Bark Surface Singularities

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Abstract

The analysis of trunk shape and, in particular, the geometric structures on the bark surface are of main interest for different applications linked to the wood industry or biological studies. Bark singularities are often external records of the history of the development of internal elements. The actors of the forest sector grade the trees by considering these singularities through standards. In this paper, we propose a method using terrestrial LiDAR data to automatically segment singularities on tree surfaces. It is based on the construction of a relief map combined with a convolutional neural network. The algorithms and the source code are available with an online demonstration allowing to test the defect detection without any software installation.

Source Code

The reviewed source code and documentation associated to the proposed algorithms are available from [the web page of this article](#)¹. The correspondences between algorithms and source codes are pointed out, and compilation with usage instructions are included in the `README.md` file of the archive.

Supplementary Material

The reference dataset, to be used for further comparisons, is provided with the article and peer-reviewed. The (non peer-reviewed) instructions to generate the learned model are provided as supplementary material on the associated [Github repository](#)².

Keywords: tree bark surface analysis; singularity segmentation; relief map; LiDAR; mesh centerline; neural network; U-Net

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²https://github.com/FlorianDelconte/uNet_reliefmap

1 Introduction

The development of trees is under the control of genetic factors in interaction with different components of their environment. This development results from different meristems producing living tissues, reacting to the ambient conditions, and producing also new meristems throughout the life of the tree. Thus, buds, leaves, branches, wood and bark result from such biological processes. This ability is essential for the tree to cope with the constraints evolving during its whole life, for adapting its structure as it grows and looks for light. Of course, these constraints are dependent on climatic conditions and on competition for light, water and nutrients with the tree’s neighbors. They can also be linked to events such as frost cracking longitudinally the log, or strong wind breaking branches, or activity of insects or animals, or forester’s action. This ability produces efficient elements for photosynthesis like branches supporting leaves, but also less efficient elements like burls in Figure 1 (a). It also enables the tree to self-repair when a branch disappears as illustrated in Figure 1 (b,c,d), or when a frost crack occurs in Figure 1 (f), or when the bark is damaged during the harvesting of neighbors, as in Figure 1 (e). The result is an alteration of the internal wood structure, which can be problematic for wood use as a material, but it also coincides with a modification of the bark structure. The later provides information about the size of the internal singularity and eventually about its developmental trajectory, especially in case of branches’ scars.

The goal of this work is to automatically detect singularities (or “defects” in industrial context) located on the log surface. The detection of these singularities is an important step to determine the commercial value of trees and to optimize the processes that transform them into wood. It is not an easy task since each type of singularity presents many inter and intra species geometrical variations.

In previous work [1], we proposed a method based on the construction of a *relief map* combined with a convolutional neural network (CNN) allowing the accurate segmentation of singularities from input LiDAR 3D points of tree bark surface. In this paper, the algorithms of the proposed method are detailed together with the correspondence between algorithms and implementations. An online demonstration for testing the proposed method is available³. Moreover, we improve the generation of the *relief map* allowing to process input meshes of the partial tree bark surface. Finally, new experiments are presented in Section 4. A discussion of different parameters influence and limits for generating the *relief map* is given in Section 6. Before describing the segmentation method and algorithms, we first briefly give an overview of the main related works in the following section.

2 Related Works

In general, singularities (or defects) on the surface of a tree bark are distinguishable from the rest of the trunk because they form a local variation of relief. Singularity detection methods considered in this paper can be classified into two groups: the classical methods and the deep learning based methods.

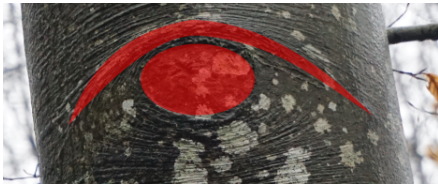
2.1 Classical Methods

In 2013, Kretschmer et al. [8] proposed a semi-automatic method for measuring branch scars on the surface of tree trunks using terrestrial laser scanning (TLS, also called topographic LiDAR) data. This method is based on a cylinder fitting along the main axis of the trunk. From this cylinder, a distance map is generated. This 2D map allows the authors to measure manually the dimensions of the branch scars on the tree surface. However, due to the non-cylindricity of the trunk, long vertical traces are observed on the distance map (see Figure 2).

³<https://ipolcore.ipol.im/demo/clientApp/demo.html?id=369>



(a) Burl (Oak)



(b) Branch scar (Beech)



(c) Branch scar (cherry tree)



(d) Little branch scar (Beech)



(e) Damaged bark (Oak)



(f) Frost crack (Oak)

Figure 1: Examples of tree bark surface singularities (also called defects): branch scar, burl and frost crack. The singularities are highlighted in red.

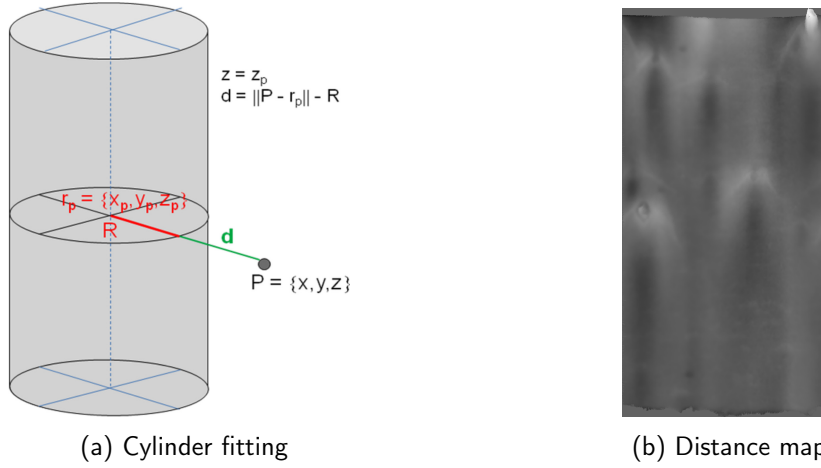


Figure 2: Singularity detection based on cylinder fitting: (a) the cylinder fitted from the point cloud, with d the distance used to compute the distance map. (b) Illustration extracted from [8].

Based on another tree bark surface representation, Nguyen et al. [11] proposed an automatic singularity segmentation method. This method takes as input a mesh reconstructed from TLS data. It builds the centerline [5] of the trunk. This centerline allows to compute a local representation of the relief at each point of the trunk mesh. Then, the automatic thresholding of Rosin [16] is used to segment the surface singularities. This method will be further detailed in Section 3.1.1. On ten meshes, the authors obtain an F1 score of 0.71. In 2020, they successfully classified the segmented regions [10] using a random forest learning process. The singularities regions were classified into four classes: branch, branch scar, bush, small singularities. The authors obtain an average of 0.86 F1 score on all classes, but only 0.46 on small singularities.

2.2 Deep-learning Based Methods

In a related context of the defect detection on surfaces of cylindrical objects, Tabernik et al. [17] proposed a method to detect surface defects on cylindrical metal parts. Grayscale intensity images of the surface are generated. A network of successive convolution layers and max pooling is used to segment cracks on the surface image. Then, a decision network made of a convolution layer and a final fully connected layer allows to decide whether or not there is a defect on the surface image. The proposed strategy is original and appears efficient for the specific case of defects on cylindrical metal parts. This is however not suitable to the singularities considered in our work.

The initial method [1] on which this paper relies can also be classified as a deep-learning based method. In particular, the learning process is performed on images generated from input meshes using the notion of *delta distance* [11]. The present strategy aims at improving the accuracy of the segmented regions. More precisely, the main idea of the method is to build a 2D view of tree bark surface from TLS data, called a *relief map* in order to train a CNN to the task of segmenting regions of particular intensities. The 2D segmentation is then redeployed back in 3D to extract the points corresponding to the singularity on the input mesh.

3 Singularity Segmentation

This section describes our method which consists of three steps (see Figure 3). Firstly, a 2D map is built from a 3D mesh of tree bark surface, called *relief map* (Section 3.1). This process stores the 3D point indexes in a 2D array, called *discretization*. In the second step, the singularities are

segmented on the *relief map* by using a deep learning process allowing to overcome the complexity of the singularity shapes (Section 3.2). For this, we consider the U-Net architecture [14]. In the last step, the segmentation is used to recover the 3D points corresponding to the singularities thanks to the discretization (Section 3.2.2).

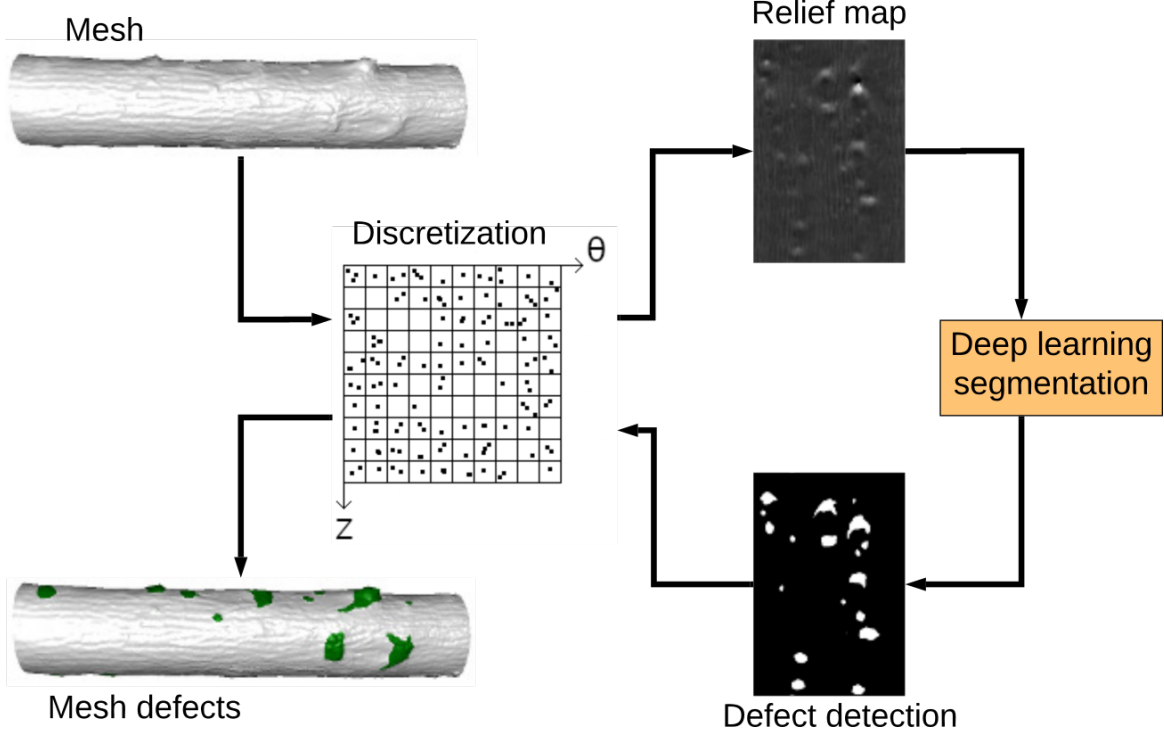


Figure 3: Pipeline of the proposed method [1].

3.1 2D Representation of 3D Mesh

3.1.1 Important Concepts from Previous Work

We recall hereafter several concepts that are used in the rest of the article: (i) centerline extraction method [5, 6], (ii) cylindrical coordinate system, and (iii) local representation of the relief with the notion of *delta distance* [11, 12].

The centerline of a trunk consists of several segments. It is obtained by accumulating along the normals of the mesh faces in a voxel space and filtering with a confidence vote. As the trunk shape can be irregular, an optimization process is performed to obtain a smooth centerline (see Figure 4).

Due to the nature of the points on the trunk surface, we consider an alternative coordinate system, called *cylindrical coordinates*, which is simply a combination of the polar coordinates in the xy -plane with the z coordinate along the centerline. It allows to easily access neighbors of points on the trunk surface. More precisely, each point in Cartesian coordinate $P(x, y, z)$ is transformed into cylindrical coordinates (r_P, θ_P, z_P) with a local coordinate system (C_i, u_i, v_i, w_i) defined for each segment C_i of the centerline, such that

- r_P is the distance between P and P' , the projection of P on the segment C_i of the centerline,
- z_P is the height of P along the centerline by summing the segment lengths of the centerline,
- θ_P is the angle between PP' and the axis v_i of the local coordinate system associated to C_i .

The delta distance, noted by δ_P , is a local representation of the tree bark relief. It is computed on a rectangular area \mathcal{P}_P around the point P (see Figure 5 (a)). The central straight line fitting the

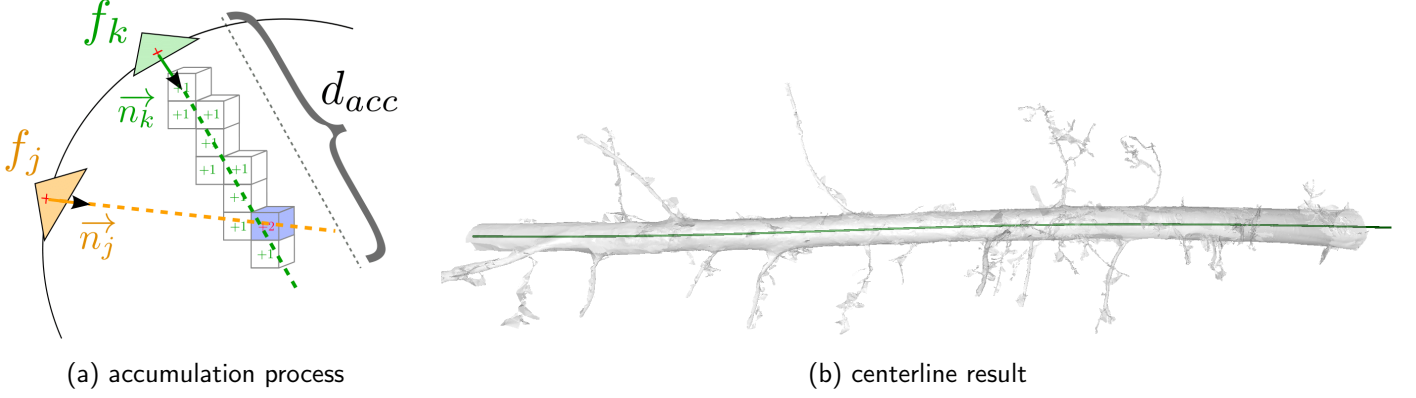


Figure 4: Illustration of the main idea of the centerline extraction algorithm: (a) accumulation step from surface faces f_k and f_j in the direction of their normal vectors (\vec{n}_k and \vec{n}_j); (b) show the resulting centerline on the whole mesh.

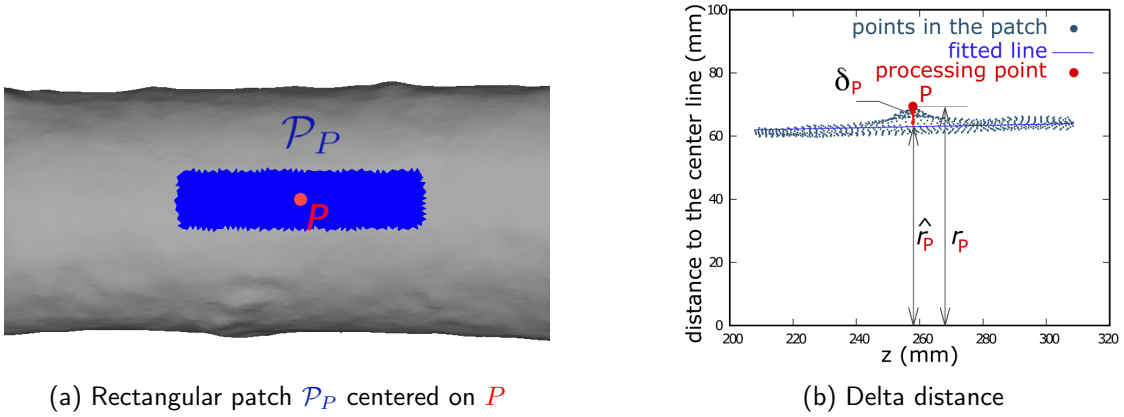


Figure 5: (a) A patch in blue, associated to the red point P , is used to compute the reference distance of this point. (b) Computation of δ_P for the red point. See [11] for more details.

points of \mathcal{P}_P is calculated by a RANSAC based linear regression. The reference distance of the point P , noted by \hat{r}_P , is the distance from the projection of P on this straight line to the corresponding segment of the centerline (see Figure 5 (b)). The difference between r_P and \hat{r}_P represents the relief of the tree bark at the point P : $\delta_P = r_P - \hat{r}_P$. More details of this part can be found in [12].

3.1.2 Discretization

The points in cylindrical coordinates are used to construct a 2D array of $height \times width$ cells storing indexes of the corresponding points. This array is called *discretizationMap*. By convention, the first (horizontal) and second (vertical) dimensions are respectively the angle θ_P and height z_P values. Thus, the *discretizationMap*'s height is equal to the trunk height. It is computed as the difference between the z components of the points having the greatest and smallest heights. The *discretizationMap*'s width, as proposed in [1], is calculated as the average circumference of the trunk, forcing our segmentation method to work on complete trunks while the calculation of the centerline can work on partial trunks (in Figure 7 (a), the centerline is built on a mesh of a partial trunk). In this work, the discretization is improved by fitting the width of the *discretizationMap* with highest arc length of the mesh. To approximate this value, we consider a binary array T initialized to 0. The size of T is set by the *Pad* parameter. This array is used to maintain an occupancy map and updated by going through all mesh points. For each point, its index i on T is computed from its θ_P angle of the

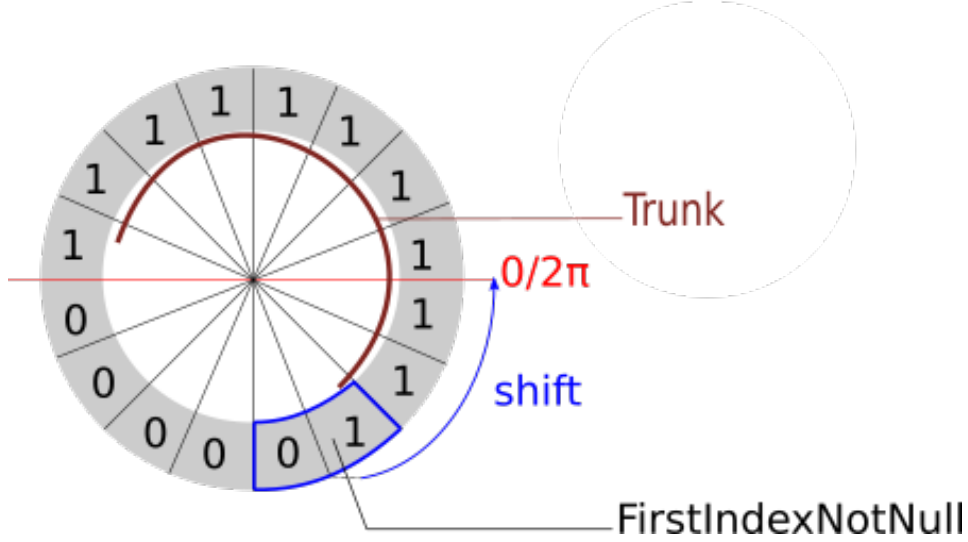


Figure 6: Computation of the partial circumference of the trunk.

cylindrical coordinate

$$i = \left\lceil \theta_P * \frac{Pad - 1}{2\pi} \right\rceil, \quad (1)$$

where $\lceil x \rceil$ represents the nearest integer to x . The array T is marked at index i of the point with value 1. Figure 6 shows an illustration of T for $Pad = 16$ where the mesh points have changed 11 array values from 0 to 1. After all points have been processed, the arc length (*discretizationMap*'s width) is computed as follows

$$width = \left\lceil 2\pi * \frac{(Pad - nbZero)}{Pad} * meanR \right\rceil, \quad (2)$$

where $nbZero$ is the total number of 0 in T , and $meanR$ is the average radii r_P of all points belonging to the trunk mesh. The $width$ value is rounded to the nearest integer.

The *discretizationMap* has $height \times width$ cells. For each point of the mesh, we compute its position, $posX$ and $posY$, of the cell in the *discretizationMap*. The position $posX$, associated with θ_P , has to take into account the first value f_1 (the closest angle to 2π or 0) which is associated with the angular interval computed from the binary array T . The trunk can be partial and therefore the angle interval can be reduced to $[f_1, upperBA - f_1]$ with $upperBA$ the angular coverage of the trunk. The value of $upperBA$ can be approximated using T

$$upperBA = \left\lceil 2\pi * \frac{(Pad - nbZero)}{Pad} \right\rceil. \quad (3)$$

An angular shift is computed to replace the interval of θ_P between $[0, upperBA]$. This shift is obtained by looking for a pattern '01' (framed in blue in Figure 6) in T . The index, $firstIndexNotNull$, is the index at the position of the cell '1' of the pattern '01'. The shift is then given by

$$shift = 2\pi - \left(\frac{firstIndexNotNull}{pad} * 2\pi \right). \quad (4)$$

Finally, $posX$ and $posY$ are given by

$$\begin{cases} posX &= \frac{width - 1}{upperBA} * ((\theta_P + shift) \bmod 2\pi - upperBA) + width - 1, \\ posY &= z_P - minH. \end{cases} \quad (5)$$

This step of discretization is described in Algorithm 1. In the code, it corresponds to the function `computeDiscretisation` of the class `UnrolledMap` in the package `ReliefMap`.

Algorithm 1: 2D discretization of the 3D tree mesh

→ see C++ code: [function computeDiscretisation of class UnrolledMap in package ReliefMap](#)

Input: 3D points in cylindrical coordinate system (height, angle, radius): *CPoints*
Input: Granularity on angle values to estimate arc length of the log: *Pad*
Output: *discretizationMap* : a 2D container with the CPoints index distributed in the cells

```

1 Let maxH be the maximum height of CPoints
2 Let minH be the minimum height of CPoints
3 Let meanR be the means of radius of CPoints
4 Let T be a binary tabular of size Pad initialized with 0 values
5 height ← (maxH − minH) + 1 // height of the relief map
6 foreach p ∈ CPoints do
7   i ← ⌈p.angle * pad / 2π⌉ // round to nearest
8   T[i] ← 1
9 find ← false // boolean value to search '01' pattern in T
10 FirstIndexNotNull ← 0 // store the '1' index in '01' pattern found
11 id ← 0 // current index to loop over T
12 while !find or id < Pad do
13   currentValue ← T[id]
14   nextValue ← T[(id + 1) mod (pad − 1)]
15   if currentValue = 0 and nextValue = 1 then
16     find ← true
17     FirstIndexNotNull ← id + 1
18   id ← id + 1
19 Let nbZero the number of zeros in T
20 width ← ⌈2π * (Pad − nbZero / Pad) * meanR⌉ // width of the relief map
21 upperBA ← (Pad − nbZero / Pad) * 2π // upper bound of angle in CPoints
22 shift ← 2π − (firstIndexNoNull / pad * 2π) // shift to apply on CPoints
23 Initialize discretizationMap to [height, width]
24 for i = 0 to CPoints.size() − 1 do
25   shiftedCurrentAngle ← (CPoints[i].angle + shift) mod 2π // apply shift and use modulus
25   currentHeight ← CPoints[i].height
26   posX ← (width − 1 / upperBA) * (shiftedCurrentAngle − upperBA) + width − 1
27   posY ← currentHeight − minH
28   discretizationMap[posY][posX] := i // push current index in the cell

```

3.1.3 Relief Map

From the 2D structure – the *discretizationMap* – containing for each cell a set of index points, we will build an image in which the intensity of each pixel is calculated with the corresponding cells in the discretization. It is called a *relief map*. In the following, we describe the multi-resolution process (Algorithm 2) allowing to generate the graylevel *relief map* with fixed scale from the *discretizationMap*.

The *relief map* is built through the discretization process. The map domain is rectangular but the trunk does not necessarily cover the whole area. During the loop over the *discretizationMap* cells,

we check if a pixel could be represented by an intensity. This consists in trying to reach the edges of the *discretizationMap*, if at least one cell is not empty during the process, then the pixel could be represented by an intensity. We see in Figure 7 (b), a *relief map* obtained from a partial trunk, the red pixels are those whose intensity will not be calculated during the discretization process. Algorithm 3 is used to check if a cell of the *discretizationMap* could be represented. The function corresponding to this algorithm is `detectCellsIn` in the class `UnrolledMap` of the package `ReliefMap`.

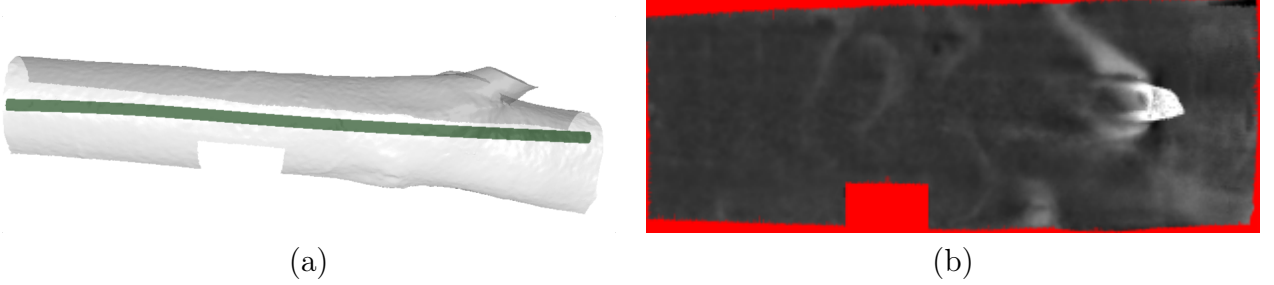


Figure 7: (a) Partial mesh with centerline in green. (b) Partial *relief map* with outside pixels in red.

For each cell, a value is chosen according to the delta distance (δ_P) of points in the cell. This distance δ_P represents the local relief of each point, its calculation is detailed in [11] and reported in Section 3.1.1. If the current cell is not empty in the *discretizationMap*, we choose the maximum δ_P of all points contained in the cell. Otherwise, a multi-resolution analysis is performed. It consists in looking for the missing information in cells resulting from the *discretizationMap* reduced by a factor $\frac{1}{2^n}$, with $n = 1, \dots, MaxdF$ until the cell contains at least one point ($MaxdF$ is a parameter of the multi-resolution search function, it allows to limit the search). More precisely, the points contained in the larger cells are obtained by accumulating those of the unreduced cells of the *discretizationMap* on a square window of width 2^n . Finally, we choose the maximum δ_P of points contained in the studied cell. Algorithm 5 allows to extract the points in lower resolution and Algorithm 4 gives the maximum relief representation of a set of points. They correspond respectively to the functions `getIndPointsInLowerResolution` and `maxReliefRepresentation` in the class `UnrolledMap` of the package `ReliefMap`.

A grayscale image is generated from *relief map*, by using a single static intensity scale where *intensityPerCm* grayscale levels correspond to one centimeter. Associated to this parameter, a cutoff interval of minimal and maximal heights ($[minRV, maxRV]$) is considered to ensure that all levels can be represented in the usual $[0, 255]$ range. The minimal value *minRV* is a parameter of our method and the maximal value *maxRV* is simply given by

$$maxRV = 255 * \frac{1}{intensityPerCm} + minRV. \quad (6)$$

The resulting grayscale value is deduced as follows

$$grayscaleValue = \frac{reliefValue - minRV}{maxRV - minRV} * 255. \quad (7)$$

Algorithm 6 allows to generate the grayscale *relief map*. It is implemented in the function `toGrayscaleImageFixed`, in the `UnrolledMap` class of the package `ReliefMap`.

3.2 2D Segmentation

The *relief map* allows a 2D representation of the trunk. The 3D problem of surface singularity detection becomes a 2D problem of binary-image-classification in which each pixel of the *relief map*

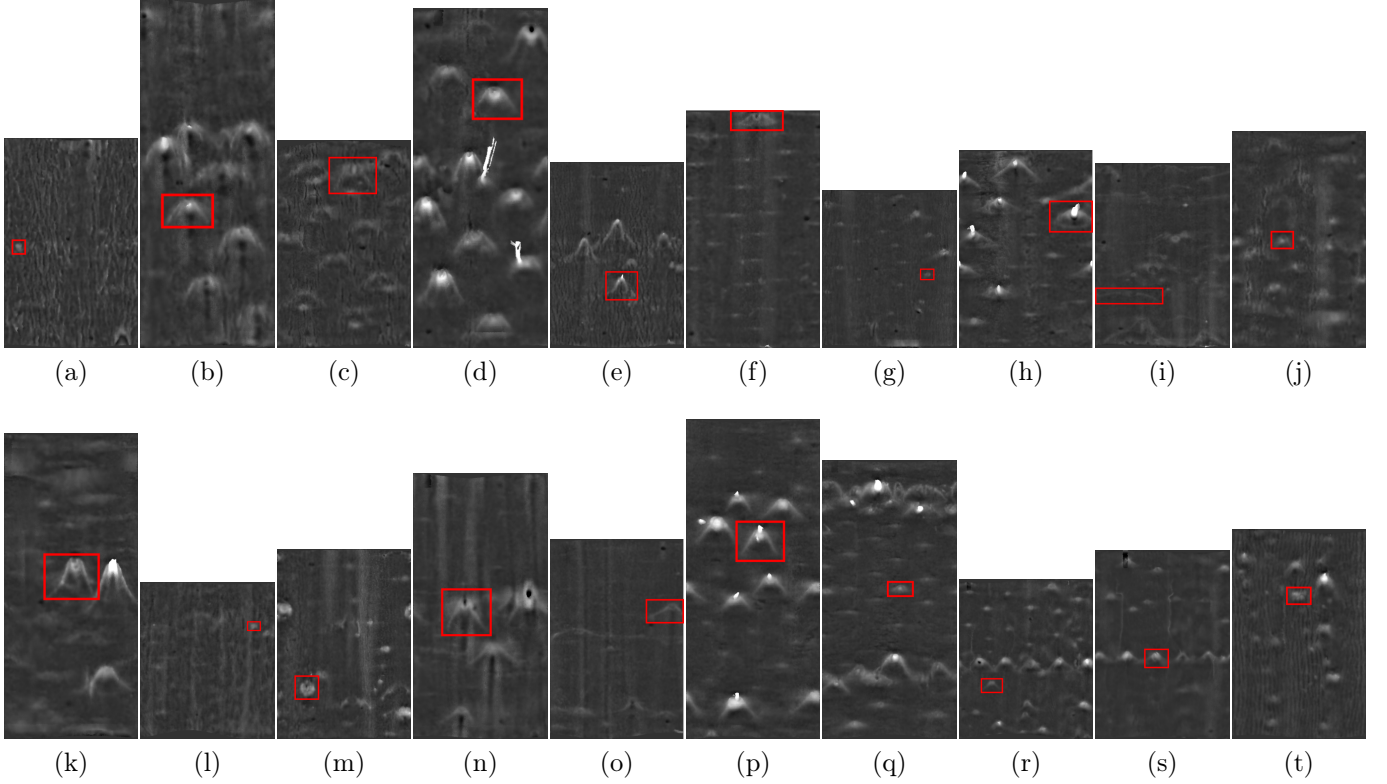


Figure 8: Examples of relief maps after multi resolution analysis. White color for stronger reliefs. Examples of singularities are highlighted in red frames, one singularity per *relief map*. Here is the correspondence between *relief map* and tree species: (a,b,c,d)=Alder, (e,f,g,h)=Aspen, (i)=Beech, (j,k)=Birch, (l)=Horn beam, (m)=Linden, (n,o)=Red oak, (p,q)=Wild cherry, (r,s)=Fir, (t)=Elm.

Algorithm 2: Multi resolution analysis to compute missing information for empty cells
 → see C++ code: `computeNormalizedImageMultiScale()` of class `UnrolledMap` in package `ReliefMap`

Input: Maximum resolution to reach during analysis : $\frac{1}{2^{MaxdF}}$

Output: *reliefImage* : 2D image of the relief

```

1 Let height and width be the height and width of discretizationMap
2  $dF \leftarrow 1$  // actual decrease resolution factor
   needDisplay  $\leftarrow$  false
4 for  $i = 0$  to height - 1 do
5     for  $j = 0$  to width - 1 do
6         needDisplay  $\leftarrow$  detectCellsIn(i,j) // see Algorithm 3
7         if needDisplay then
8             relief = maxReliefRepresentation(i,j,0) // see Algorithm 4
9              $dF \leftarrow 1$ 
10            while relief = -1 and  $dF < MaxdF$  do
11                relief  $\leftarrow$  maxReliefRepresentation(i,j,dF) // relief of the current cell at  $\frac{1}{2^{dF}}$ 
12                 $dF \leftarrow dF + 1$ 
13            reliefImage[i,j]  $\leftarrow$  relief
    
```

Algorithm 3: Verify whether the cell is on the trunk

→ see C++ code: `detectCellsIn()` of class `UnrolledMap` in package `ReliefMap`

Input: Index of the studied cell : (i, j)

Input: 2D Discretization of the 3D points : *discretizationMap*

Output: *CellsIn* : Boolean, true if one cell is considered on the trunk

```

1 CellsIn  $\leftarrow$  true
2 iUp  $\leftarrow$  i
3 IndsCell  $\leftarrow$  discretizationMap[i][j]
4 while IndsCell is empty and (iUp > 0) do
5   | iUp  $\leftarrow$  iUp - 1                                     // Decrement to reach the top
6   | IndsCell  $\leftarrow$  discretizationMap[iUp][j]
7 Let iDown, jLeft, jRight be the reached index obtained by the same procedure to reach both
  left and right respectively
8 if iUp = 0 and IndsCell is empty then
9   | same check for iDown, jLeft, jRight
10  | CellsIn  $\leftarrow$  false

```

Algorithm 4: Compute relief representation at one cell in specified resolution

→ see C++ code: `maxReliefRepresentation()` of class `UnrolledMap` in package `ReliefMap`

Input: Index of the studied cell : (i, j)

Input: Decrease resolution factor : dF

Input: Relief representation for each 3D point: *reliefRepresentation*

Output: *maxRelief* : relief representation of one cell with a specified resolution

IndexesInCell \leftarrow `getIndPointsInLowerResolution(i, j, dF)` // see Algorithm 5

```

2 if IndexesInCell is not empty then
3   | maxRelief  $\leftarrow$  search for the maximum relief value in IndexesInCell
  else
5   | maxRelief  $\leftarrow$  -1                                     // conditional value
                                     // Same procedure for to compute the mean or median relief representation

```

Algorithm 5: Search indexes in discretization map at one cell in lower resolution

→ see C++ code: `getIndPointsInLowerResolution()` of class `UnrolledMap` in package `ReliefMap`

Input: Index of the studied cell: (i, j)

Input: Decrease resolution factor: dF

Input: 2D Discretization of the 3D points: *discretizationMap*

Output: *outPutInd* : Index of the 3D points in a cell at a lower resolution

```

1 down_factor  $\leftarrow$   $2^{dF}$ 
2 i_topLeftCorner  $\leftarrow$  (i/down_factor) * down_factor
3 j_topLeftCorner  $\leftarrow$  (j/down_factor) * down_factor                                     // round to lowest integer
4 for k = i_topLeftCorner to i_topLeftCorner + down_factor do
5   | for l = j_topLeftCorner to j_topLeftCorner + down_factor do
6     | | if k < height and l < width then
7       | | | outPutInd := discretizationMap[k][l]                                     // push indexes at pos (k, l)

```

Algorithm 6: Convert to grayscale image with fixed scale

→ see C++ code: `toGrayscaleImageFixed()` of class `UnrolledMap` in package `ReliefMap`

Input: Number of intensity to represent 1 cm : *intensityPerCm*

Input: Minimal relief representation *minRV*

Input: 2D image of the relief : *reliefImage*

Output: *grayScaleReliefImage* : Grayscale image of the relief

```

1 maxRV ← (255 * (1/intensityPerCm)) + minRV           // Maximal relief representation
2 Let grayScaleReliefImage get the same size than reliefImage
  foreach pixels ∈ reliefImage do
4   reliefValue = reliefImage(point)
5   if reliefValue < minRV then
6     | grayscaleValue ← 0
   else if reliefValue > maxRV then
8     | grayscaleValue ← 255
   else
10    | grayscaleValue ← ((reliefValue − minRV)/(maxRV − minRV)) * 255
11  grayScaleReliefImage(pixel) ← grayscaleValue

```

will be classified as singularity or not. We can see in Figure 8 that singularities on tree barks may have arbitrary size, shape and orientation. Furthermore, the roughness of the tree bark, the variability of singularities for the same species and between different species make the detection task difficult to automate by conventional segmentation algorithms. To overcome this, we opted for a segmentation by a supervised deep learning approach. In Section 3.2.1, we explain the generation of training pairs (example/label). Section 3.2.2 details the trained CNN architecture of U-Net [15].

3.2.1 Training Data

The singularities (or defects) have been hand-segmented on the meshes (and verified by experts). This information allows to associate to each *relief map* an image labeled in black and white. The passage of 3D points to 2D labeled image is done by a similar process as described in Section 3.1. The difference is that, instead of using δ_P to represent reliefs in gray level, the pixels corresponding to the singularities have intensity 255 (white) and the others have intensity 0 (black). Besides, as can be seen in Figure 9 (a), some pixels belonging to the singularities remain black. The multiresolution process is not used here because it would tend to enlarge the singularities. Instead, a closing and opening operation with a kernel of size 3×3 is applied on the labeled image (see Figure 9 (b)). In Figure 9 (c) we see the resulting *relief map* associated to the labeled image.

The size of the *relief map* (and the labeled images) is different from one mesh to another because the circumference and height of the trunk are not always the same. To increase the number of training data, we have extracted patches of size 320×320 pixels following two strategies:

- 1) with singularities: the process consists in finding the barycenters of connected components in the labeled images. For each barycenter, we extract a centered patch of size 320×320 pixels in both labeled image (as ground-truth) and *relief map*. If a singularity is too close to the edge of the image, a translation is performed so that the patch still contains the singularity and is included in the image (see Figure 10).
- 2) without singularities: the process consists in finding rectangular areas of size 320×320 pixels containing no white pixels in the labeled image. When such an area is found, the patch is

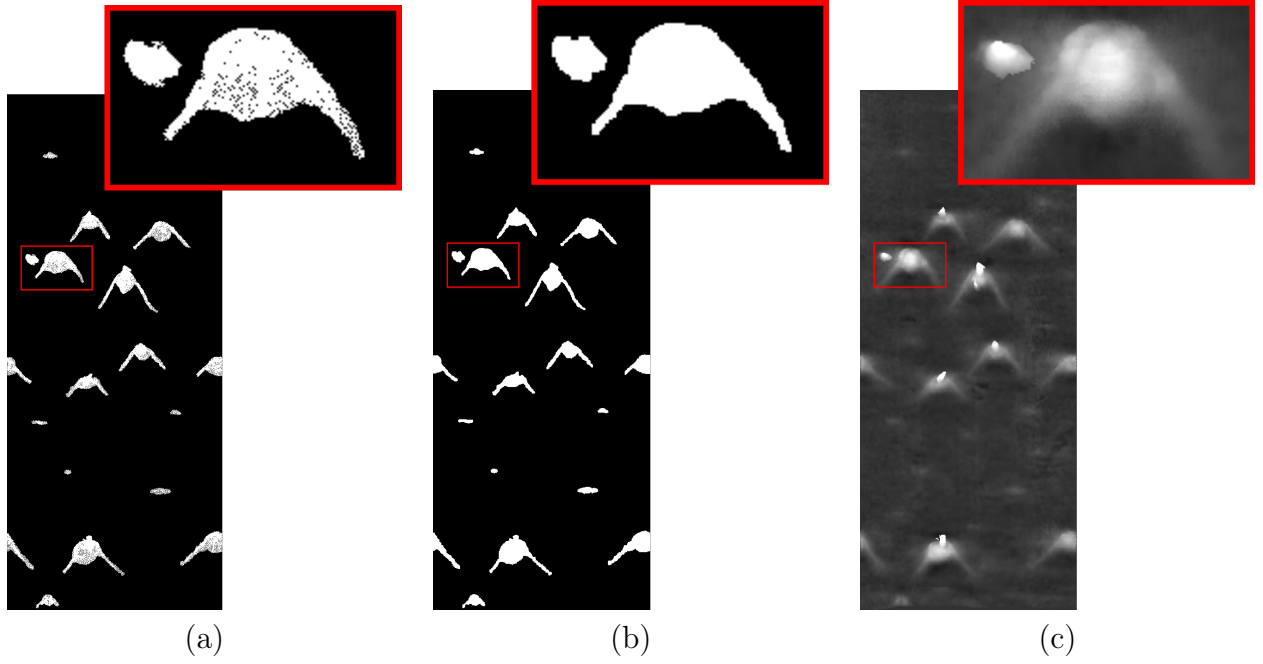
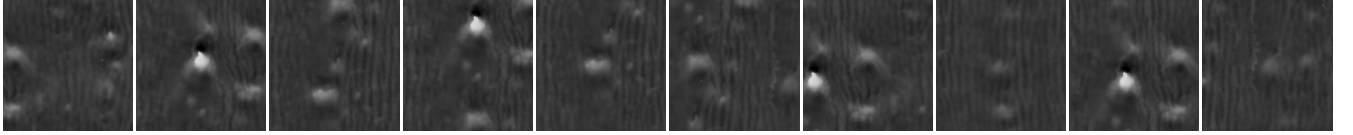


Figure 9: labeled image and corresponding *relief map* with zoom in rectangular area: (a) before closing and opening operation, (b) after closing and opening operation and (c) corresponding *relief map*.



(a) Extracted patches with singularities from relief maps



(b) Extracted patches with singularities from annotated maps

Figure 10: Some samples from training data.

extracted in the *relief map* and a black image is generated as ground-truth.

Following this splitting process, different techniques were also applied on the resulting patches to enlarge further the data. In particular, we consider the following operations: rotation in range 0° to 20° , flipping vertically and horizontally, zooming of $\pm 30\%$ and randomly deleting a rectangular area [2] with a 0.5 probability. Note that this data augmentation is performed on the fly, i.e., during the training process.

3.2.2 U-Net Architecture for Segmentation

U-Net is a fully convolutional network. It is widely used in bio-medical image segmentation [3, 19, 20]. More recently, U-net has been applied in other fields such as satellite image segmentation [4, 18] or tunnel object detection [13]. This architecture is well-known for its performance when trained with very few images.

In general, a U-net network consists of two parts: encoding and decoding. The encoding part looks like a classical convolutional network architecture. It consists in applying successively convolutions

and max pooling operations. The decoding part is made of up-sampling operations followed by a concatenation with the layer of the same level in the encoding part.

For our problem of detecting tree bark surface singularities, we made several changes to the original U-Net. In order to reduce the over-fitting of the considered neural network, we apply a regularization technique, called *drop-out*. More precisely, two dropout layers are added, with a 0.5 probability, to randomly drop some of the connections between layers. At the first level, there are 32 filters per convolution layer. Then the number of filters is doubled at each level. Besides, due to the dying ReLU problem [9] the Leaky ReLU activation function is employed instead of ReLU from the original architecture. Finally, in the last layer, we use a sigmoid activation function instead of the soft-max function to ensure the output pixel values range between 0 and 1. The proposed network architecture is illustrated in Figure 11.

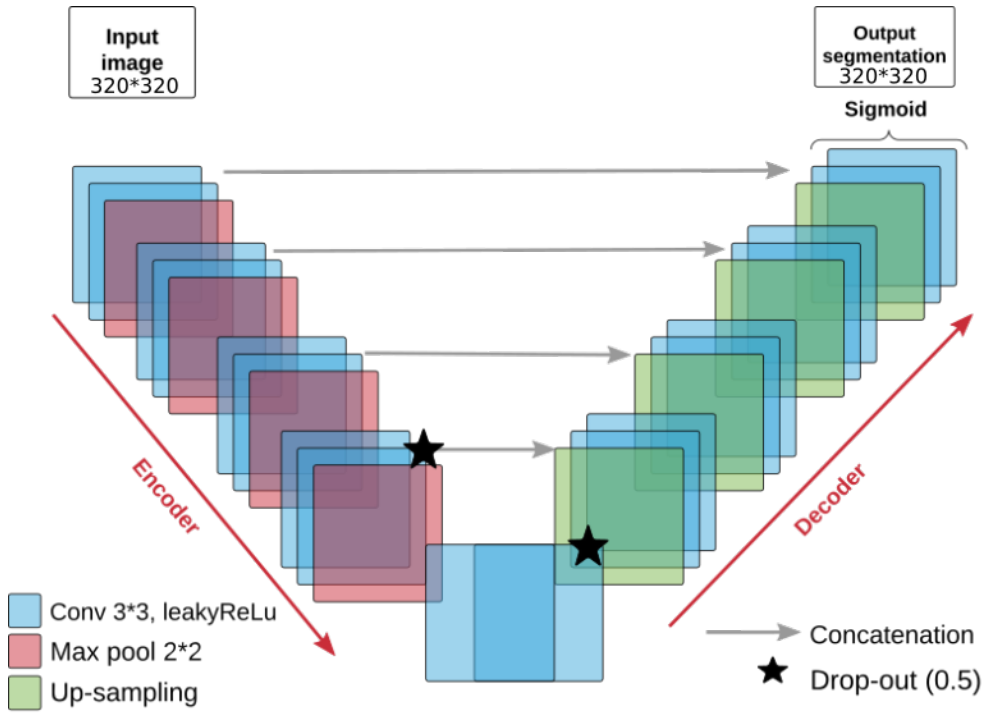


Figure 11: The architecture for tree bark singularities detection based on U-Net [15].

Once trained, the network’s prediction produces an image whose pixel intensity corresponds to a probability score of belonging to a singularity pixel. The higher the grey level, the more the pixel is considered as a singularity by the network and vice versa. We can see in Figure 12 two examples of output of the trained network.

From the prediction result, a threshold is applied to retrieve a 2D segmented image in black and white. The white pixels correspond to the regions of the *relief map* considered as singularities. In order to obtain the singularities on 3D mesh from white pixels of the segmentation results, an inverse discretization is performed. More precisely, the discretization has the same size as the segmentation. The indices of the points contained in the cells of the discretization at the position of the white pixels are extracted. They correspond to the singularities in 3D. In Figure 12, we can see two examples of extracted points in green color from the segmented results.

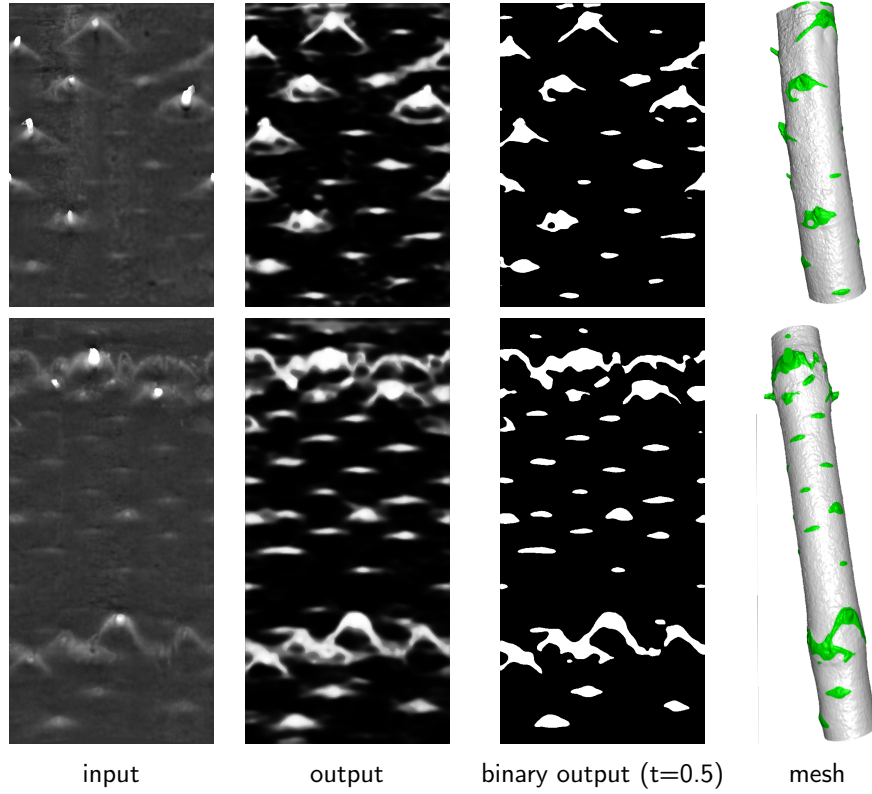


Figure 12: Examples of output of our U-net [15] inspired architecture.

4 Experiments

4.1 Dataset

To test our method we have 25 trunk meshes: 10 from [11] and 15 new data manually annotated. This database contains 11 tree species: beech, birch, elm, fir, red oak, wild cherry, aspen, horn beam, lime, and alder. The studied trunks have between 366 and 896 cm of circumference and between 694 and 1150 cm of height. The visible surface singularities are mainly branch scars and burls, there are also some small singularities whose type is not distinguishable. In Figure 13, we can see some examples of 3D point clouds from the dataset. We randomly pick 5 trunks among the 25 to test the method and kept the others for training.

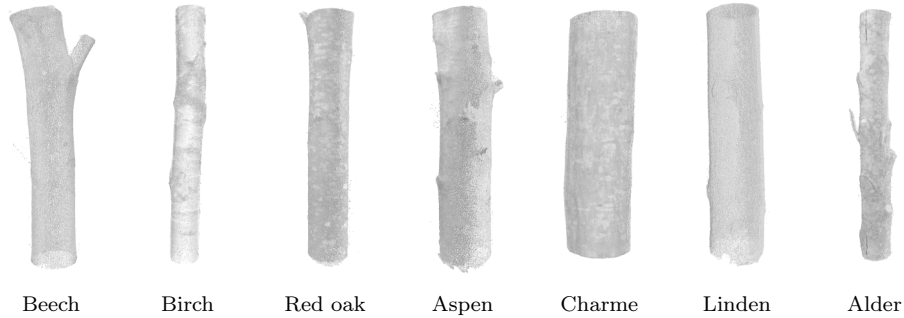


Figure 13: Examples of trunks (logs) of different tree species, captured from LiDAR point cloud including reflectance values.

4.2 Cross-validation Studies

The cross-validation consists in training k models by varying the data used for training and validation in such way that the model is validated on k different folds. In our experiment $k = 5$. The *relief maps*, generated from the training data, are split into patches of 320×320 pixels (see Section 3.2). After the splitting process, we obtain 456 patches. Five models are trained on groups of patches with a ratio of $\frac{1}{5}$ for the validation and the rest for the training. These groups of patches are constructed so that the validation data is different for each model. Once the network is trained, we apply the segmentation method (see Section 3) on the 5 test trunks, and obtain a set of points classified as singularities. They are then compared to the ground-truth. It should be mentioned that, in [1], we performed a cross validation on the same data. However, the experiment was different, we wanted to test our method on all the available data. Here, the cross validation allows us to test the performances of the segmentation model and its sensibility to the learning data. Figure 14 summarizes the difference between the two cross validation procedures on a base of ten examples.

The training process was performed on a GPU (NVIDIA Geforce RTX 2080Ti with 12Go RAM). We used the Adam optimiser [7] with the two parameters $\beta_1 = 0.9$ and $\beta_2 = 0.99$ (default values in tensorflow), and set the learning rate at 0.0001. We trained our network for 40 epochs, each epoch comprised 111 steps with 10 images per batch. As for the parameters dropout rate δ and Leaky ReLu activation α , several values have been tested, and we come out with $\delta = 0.5$ and $\alpha = 0.01$ for the smallest loss function (binary cross entropy) on the validation set. It should be mentioned that our training is quite fast, it takes about 14 seconds per epoch.

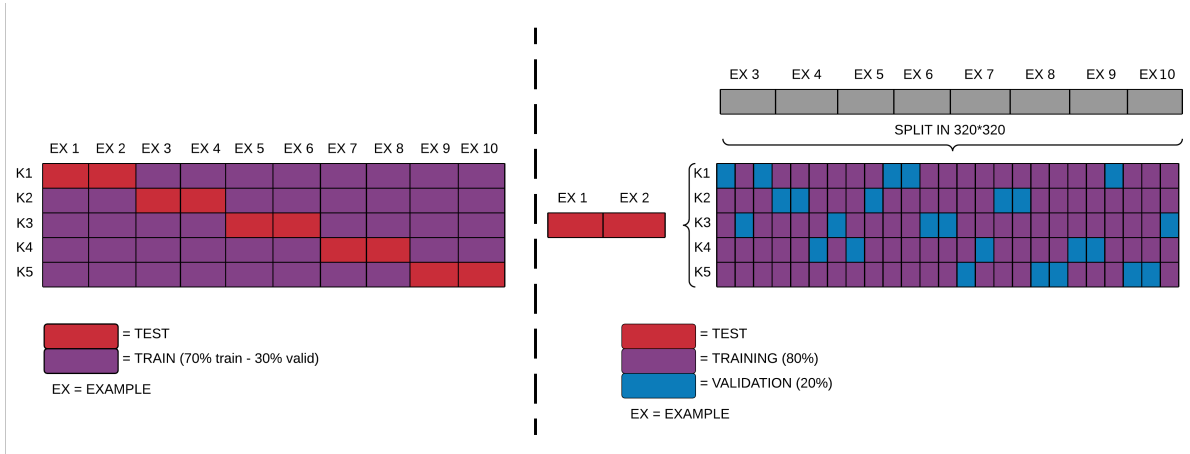


Figure 14: Difference between the cross validation in [1] (left) and our cross validation (right).

4.3 Results

The results are presented in Table 1. For evaluating the method, 3 metrics are used: precision, recall and F1 score. Each row contains the results of the training model on the test data. The average and standard variation are calculated over the 5 models. Figure 15 shows the segmentation results of our method (using $K4$ as model segmentation) with a comparison to the ground-truth. On the examples WildCherry1, Redoak1 and Fir1, we obtain an average F1 score > 0.815 . The F1 score is lower on Aspen2 and Alder2. For Aspen2, we notice a decrease of the recall value compared to the other examples. The regions segmented by our method correspond well to singularities, however the ground-truth covers wider zones of defects. This results in an increase of the false negative rate and a decrease of the recall value. For Alder2, it is the precision value that is lower. Around the branch scars, the trunk forms cavities. Our segmentation method tends to encompass these

structures which increases the false positive rate and therefore the accuracy decreases. Despite this difference in performance, the low values of standard variation show that the 5 models provide close performance measures even for Aspen2 and Alder2. This makes us believe that the training is robust to the considered dataset.

K-Folds	WildCherry1			Redoak1			Fir1			Aspen2			Alder2		
	prec	recall	F1	prec	recall	F1	prec	recall	F1	prec	recall	F1	prec	recall	F1
K0	0.825	0.88	0.851	0.893	0.886	0.889	0.831	0.815	0.822	0.877	0.561	0.682	0.594	0.878	0.707
K1	0.837	0.829	0.831	0.867	0.861	0.863	0.867	0.731	0.79	0.816	0.545	0.652	0.567	0.799	0.663
K2	0.831	0.868	0.848	0.878	0.877	0.877	0.857	0.778	0.814	0.894	0.611	0.725	0.593	0.831	0.691
K3	0.846	0.862	0.853	0.853	0.889	0.87	0.854	0.802	0.826	0.849	0.609	0.709	0.6	0.86	0.706
K4	0.811	0.911	0.857	0.871	0.906	0.888	0.827	0.82	0.823	0.88	0.636	0.737	0.596	0.885	0.711
Mean	0.83	0.87	0.848	0.872	0.884	0.877	0.847	0.789	0.815	0.863	0.592	0.701	0.59	0.851	0.696
Std	0.013	0.03	0.01	0.015	0.016	0.011	0.017	0.036	0.014	0.031	0.038	0.034	0.013	0.036	0.020

Table 1: Cross validation results for the considered 5 folds.

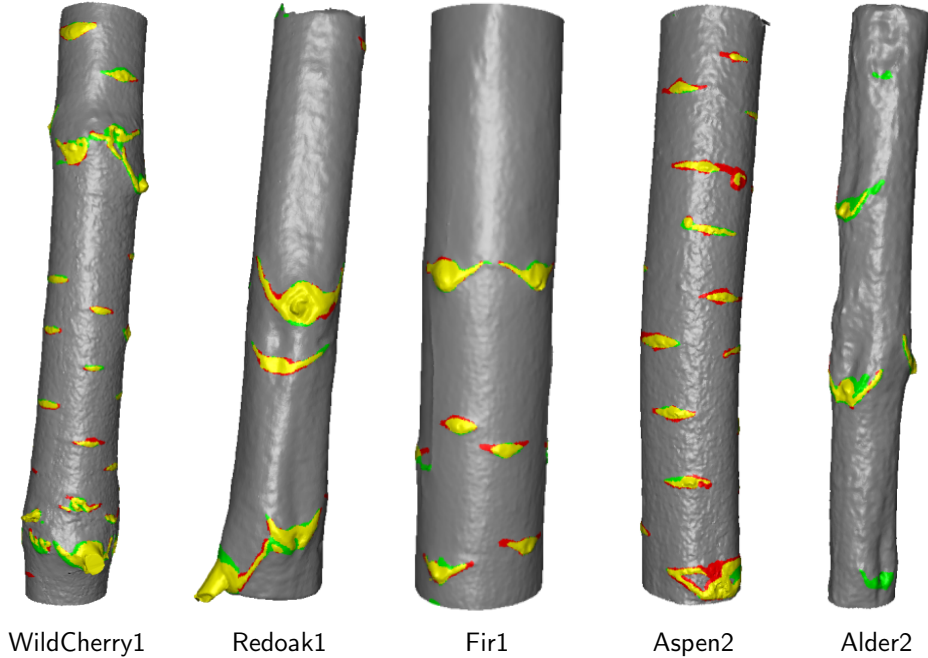


Figure 15: Colorized mesh to show the difference between the ground-truth and segmentation obtained with the proposed method. Yellow is true positive, red is false negative and green is false positive.

5 Code

The code is written in C++ and python. The C++ part allows the interaction between mesh and *relief map*. The python part allows to use the segmentation model. In addition, the user can reproduce the results in Table 1.

5.1 Materials

The archive `examples_IPOL.tar.gz` contains the tree meshes and the ground-truth data files. They are in two directories: `INRAE1a`, `INRAE1b`. The data come from the same acquisition device and have

been transformed into a 3D mesh using the process described in [10]. Each tree trunk is associated to three files: the mesh (with extension `.off`), the point indices corresponding to singularities (suffixed by `-groundtruth-points.id`), the face indices corresponding to singularities (suffixed by `-groundtruth.id`). The experiments in Section 4 use the files suffixed by `-groundtruth.id` for evaluating the performance of our method. The `scaledMeshes` directory contains scaled meshes used in Section 6.4.

The archive `model_IPOL.tar.gz` contains the models to reproduce the results. They are suffixed by `K` following a number between 0 and 4. Images in Section 4 are generated from the model `k4.hdf5`.

5.2 Dependencies

For compilation of the C++ sources these libraries must be installed:

- DGtal 1_1_0 or later: <https://github.com/DGtal-team/DGtal>
- GNU GSL: <https://www.gnu.org/software/gsl/>
- PCL: <https://pointclouds.org/downloads/>

To use our trained model for the segmentation of singularities on the *relief map* these libraries need to be installed (we recommend the user to use a virtual environnement as described in the tensorflow guide):

- Tensorflow 2.2: <https://www.tensorflow.org/install/pip>
- tensorflow-addons: <https://www.tensorflow.org/addons/overview>
- OpenCv: <https://pypi.org/project/opencv-python/>

5.3 Generate the Relief Map (C++)

Once the dependencies are installed and the sources downloaded, the project is built with the following commands:

```
cd TLDDC
mkdir build
cd build
cmake .. -DDGtal_DIR=/path/to/DGtalSourceBuild
make
```

Three executable files are generated in the **build** directory: *segunroll*, *groundtruth*, *segToMesh*.

segunroll allows the user to build the grayscale *relief map*. The image format is `pgm`. Three files are generated: `reliefmap_info`, `cylPoint`, `discretize`. The file `reliefmap_info` contains data relative to the construction of the *relief map*: height, width, upper bound of the angle of the mesh points (see Section 3.1.2). All the points of the mesh converted into cylindrical coordinates are stored in `cylPoint` using one point per line with: radius, angle and height. The file `discretize` contains $height \times width$ lines. Each line contains the list of indices of points belonging to the cell of the discretization (-1 if none). We save this information to avoid having to recalculate it later. The user can use the following command to generate the *relief map*:

```
./segunroll -i InputMesh [-h] [CenterlineParameters] [ReliefMapParameters] -o outputName
```

- *InputMesh*: path to a trunk mesh.

- *-h*: option for the command line helper.
- *CenterlineParameters*: chosen according the recommended values in [10].
- *ReliefMapParameters*: parameters for *relief map* (*--MaxdF*, *--minRV*, *--intensityPerCm*, *--pad*). They are also set with default values.
- *-o*: prefix of the output.

For example, you can use this command to reproduce the same relief map used in our experiments:

```
./segunroll -i INRAE1a/WildCherry2.off -o WC2 -MaxdF 4 -minRV -5 -intensityPerCm 10 -pad 200
```

groundtruth allows the user to generate a *pgm* image of the same size as the *relief map* in black and white with white for the position of defects on the map. For this, the information previously calculated and stored in *reliefmap_info* and *cylPoint* is used. These labeled images are used to train our segmentation model, the user can generate them by using the following command (after generating the files *reliefmap_info* and *cylPoint*):

```
./groundtruth -i InputGrowthTruth -o outputName
```

- *InputGrowthTruth*: path to ground-truth, suffixed by: *-groundtruth.id*
- *-o*: prefix the output.

For example, you can use this command to reproduce the ground-truth image used in our experiments:

```
./segunroll -i INRAE1a/WildCherry2-groundtruth.id -o WC_GT
```

segToMesh allows to extract the 3D points from the output of the segmentation model. The file *discretize* allows to make the correspondence between the white pixels (for singularities) and the 3D points of the mesh (see Section 3.2.2). Two files are generated. A file suffixed by *-defect.id* contains the indices of points considered as singularities. A file suffixed by *defect.off* contains the trunk mesh with the singularities colored in green. The command to do this operation is the following (after generating the singularity segmentation by an already trained model):

```
./segToMesh -i InputMesh -s segmentationMapName -o outputName
```

- *InputMesh*: path to the same mesh used to generate the reliefmap.
- *-s*: path to the segmentation file.
- *-o*: prefix the output.

The interaction between these different executables is summarized in Figure 16.

To generate the *relief map* and labeled images of a whole directory at once, you can use the script *makeAllPair.sh* (in the *run* directory) with the following command. The *relief map* will have the same name as the mesh and the labeled image will be fixed by *_GT*.

```
./makeAllPair.sh PathToMeshDirectory OutputPath
```

- *PathToMeshDirectory*: path to the input directory containing meshes.
- *OutputPath*: path to output directory in which all samples will be moved.

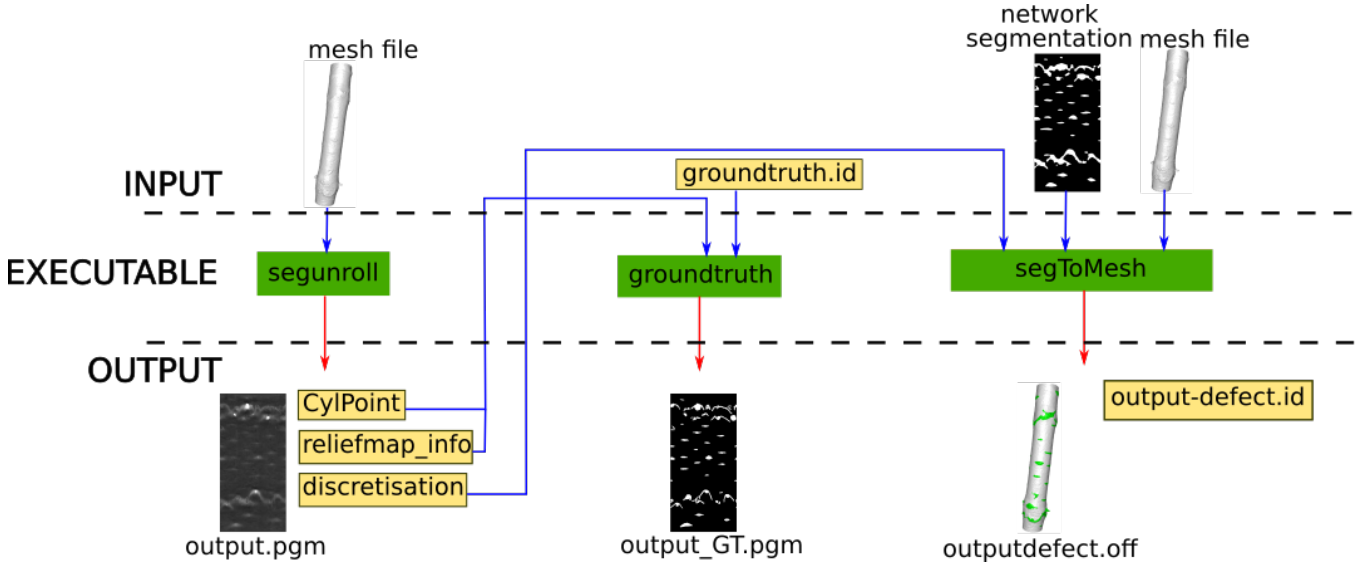


Figure 16: Interaction between the different executables of the project.

5.4 Extract Patches from ReliefMap and Ground-truth Image (python)

In the **run** directory, there is a script named *train-valid_cut.py*. From a *relief map* and a ground-truth image, it allows to extract training patches (see Section 3.2.1) and distribute them in the **train** and **valid** directories. From the created patches 80% are distributed in the train directory, and 20% in the valid directory. These directories must be created before calling the script and both of them must contain a directory named **input** and another named **output**. Here is the command to run:

```
python3 train-valid_cut.py -i PathToReliefMap -g PathToGT -o outputDir
```

- *PathToReliefMap*: path to input *relief map*.
- *PathToGT*: path to input ground-truth image.
- *outputDir*: output directory that must contain two directories named **train** and **valid**, which must contain two directories named **input** and **output**.

To perform the patches extraction on all pairs of training images in a directory (generated by the script *makeAllPair.sh*) you can use the script named *train-valid_cut_All.sh*. Here is the command to run:

```
./train-valid_cut_All.sh PathToInputDir PathToOutputDir
```

- *PathToInputDir*: path to input directory that contains *relief map* and corresponding ground-truth image suffixed by **_GT**.
- *PathToOutputDir*: output directory that must contain two directories named **train** and **valid**, which must contain two directories named **input** and **output**.

5.5 Use our Trained Network (python)

In the **run** directory, there is a script named *predict.py* that allows to use the network to segment the singularities on a *relief map*. It takes as input an already trained model and a *relief map* (previously generated) in **pgm** format. Two images suffixed by **SEG.pgm** and **SEGTRESH.pgm** are generated. The first one is in grayscale, the second one is in black and white (see Section 3.2.2). Here is the command to run:


```
python3 predict.py InputReliefMap PathToModel Threshold
```

- *InputReliefMap*: path to the relief map.
- *PathToModel*: path to the model.
- *Threshold*: threshold ([0;255]) to apply on the network prediction.

5.6 Train a Network with ReliefMap Samples (mix)

Relief map and ground-truth images must be generated by the script *makeAllPair.sh*. Here is an example of how to generate these images from the INRAE1b directory and move them to the db directory:

```
./makeAllPair.sh examples/INRAE1b/ db/
```

The learning process requires data to be organized in a directory named **train** and another **valid**. In both of them, there must be a directory named **input** and another named **output**. Create them in a directory named **db**. The network is trained on patches of size 320×320 (see Section 3.2.1), use *train-valid_cut_All.sh* to extract these patches:

```
./train-valid_cut_All.sh db/ db/
```

Once data is prepared, train the network with the script named *train.py*. Here is the command:

```
python3 train.py -i db/ -o prefix
```

- *db/*: database directory that contain train and valid sample.
- *prefix*: name of the model.

5.7 Test the Complete Process of our Segmentation Method (mix)

In the **run** directory, there is a script named *deep-segmentation.sh*. This script allows to call in succession: *segunroll*, *predict.py*, *segToMesh*. Here is the command to execute it:

```
./deep-segmentation.sh PathToModel PathToMesh
```

- *PathToModel*: path to the model.
- *PathToMesh*: path to the mesh.

5.8 Reproduce the Results (mix)

In the **run** directory, there is a script named *testK_folds.sh*. This script allows to reproduce the results in Table 1. The segmentation method is tested on 5 examples and 5 models. The name of the tested mesh is written in the file **testKFold_Path.txt** at the root of the code repository. The scripts *segunroll*, *predict.py*, *segToMesh* are called to extract the singularity points of the mesh. The metrics (precision, recall, F1) are displayed, for each fold, in the terminal. Here is the command to execute it:

```
./testK_folds.sh PathToMeshDirectory PathToModeleDirectory
```

- *PathToMeshDirectory*: path to the root of downloaded mesh directory.
- *PathToModeleDirectory*: path to the root of model directory.

6 Influence of Parameters and Limits

The *relief map* is the main tool of our method. It greatly influences the quality of the singularity segmentation. To generate a *relief map*, there are 4 important parameters. In the following, we describe the role and the default values of these parameters.

6.1 Depth Parameter in Multi-resolution Analysis: MaxdF

A multi-resolution analysis is performed on the *relief map*. The purpose of this analysis is to complete the *relief map* with information at lower resolution (see Section 3.1.3). During this operation, the dimensions of the *relief map* are reduced by a factor of $\frac{1}{2^n}$ with $n \in [0, \dots, MaxdF]$. In Figure 17, we can see 5 *relief maps* coming from the same mesh at different resolutions which decrease by a factor of two. At the resolution 1, we can see “holes” (pixels with no value) on the *relief map*, this missing information will be completed by analyzing the *relief map* at a smaller resolution. By reducing the resolution of the *relief map*, the information it contains is reduced as well (the relief is less well represented). We stop the multi-resolution search, when the resolution becomes too small. The *MaxdF* parameter allows us to stop this search. If $n = MaxdF$, the multi-resolution process is stopped at the first level. In our data, the smallest resolution reached by the multi-resolution analysis is $\frac{1}{2^4}$. Therefore, we set $MaxdF = 4$ as the default value.

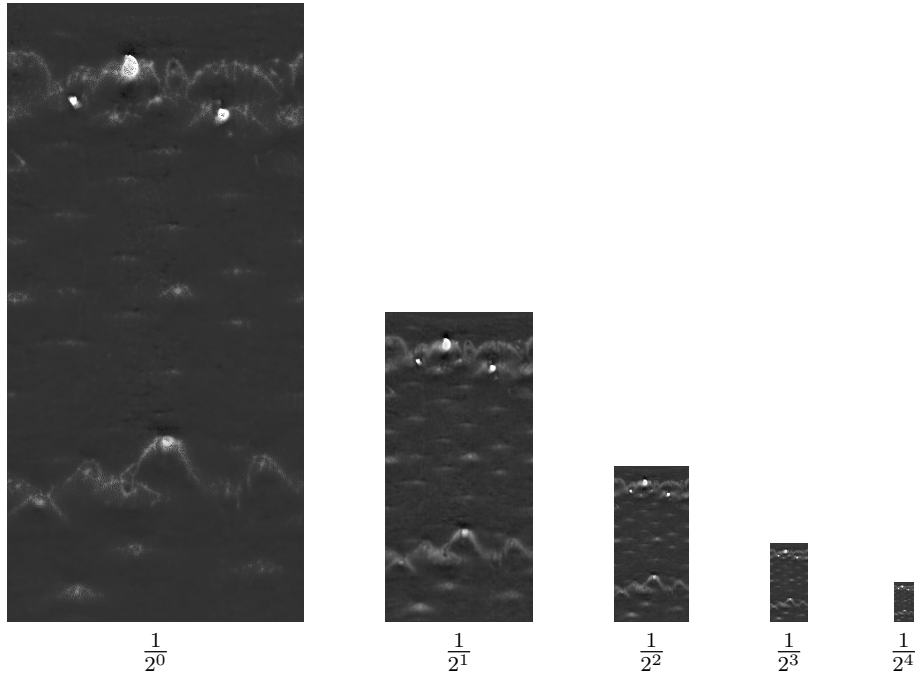


Figure 17: Same relief map with resolution decreasing by $\frac{1}{2^n}$ factor with $n \in [0, \dots, 4]$.

6.2 Grayscale Parameters: `intensity_per_cm` and `minRV`

The singularities are distinguishable from the rest of the trunk because they form a relief variation on the surface. This variation can be negative or positive. To represent the surface relief variation, we consider a grayscale *relief map*. This conversion is done by two parameters: `intensity_per_cm` and `minRV`. The parameter `minRV` corresponds to the intensity 0 of the *relief map* for the smallest relief to represent. It is recommended to use a negative value for `minRV`, this allows to represent the whole surface of the trunk. The parameter `intensity_per_cm` allows to define the number of gray levels to represent 1 cm of relief. The choice of the value of `intensity_per_cm` should not be too high because it determines the maximum representable relief. If `intensity_per_cm` = 50, the *relief map* will be able to represent at most a relief about 5 cm. The value must not be chosen too low either because some singularities have a very low relief, for example the singularity named “picots” are not more than 1cm high. By default, `intensity_per_cm` = 10 and `minRV` = -5 for all the *relief maps* generated for the training or for the tests of the segmentation method.

6.3 Angular Division Parameter: `Pad`

The width of the *relief map* corresponds to the maximum arc length of the mesh. To estimate it, we use an array of size `Pad` (see Section 3.1.2). The smaller the `Pad`, the more error will be made on the circumference of the trunk. For our data, we set `Pad` = 200 by default.

6.4 Scale Influence

It should be mentioned that the trunks in our database present comparable scale size, with hand-annotated singularities (see Section 4.1). In order to evaluate the robustness of our method with respect to the mesh scale, we have changed the scale of the WildCherry1 mesh using the following values: 0.8, 1.2, 1.5, 3, 5. This experiment is done for the purpose of verifying whether our method is able to perform the singularity segmentation on larger trunks. Figure 18 shows the *relief maps* generated from the enlarged mesh and the associated segmentation. The *relief map* seems to be impacted by the scale factor. The perturbation of the *relief map* by the scale change impacts the quality of the segmentation. We think that this is due to the fixed size of the rectangular patch used to calculate the delta distance (see Section 3.1.1). Therefore, it would be necessary to automatically adapt the rectangular patch size with respect to the studied trunk. Moreover, the *relief maps* used to train our models are generated from trunk meshes of similar size. It would be interesting to study and apply a scale variation on the training data to allow the network to generalize the segmentation on larger trunks. However, scale changes by a factor of 5 can be considered as very special cases which are infrequent for usual application cases.

7 Conclusion

In this article, we proposed a method allowing to automatically segment the singularities on the tree bark surface. It is adapted from [1]. More precisely, the method is based on the construction of a *relief map* able to locally adapt itself to the global shape of the trunk, and combines with a convolutional neural network to improve the resulting segmentation quality. Furthermore, we bring an improvement in generating *relief maps* compared to [1]. This improvement allows to build *relief maps* from partial meshes of trunks where a cylindrical sector may be missing. Moreover, we detail the algorithms and the code used to generate the *relief map*. The cross validation shows that the training is robust to our database (the standard deviation is low). However, we believe that our segmentation method would benefit from using more 3D information.

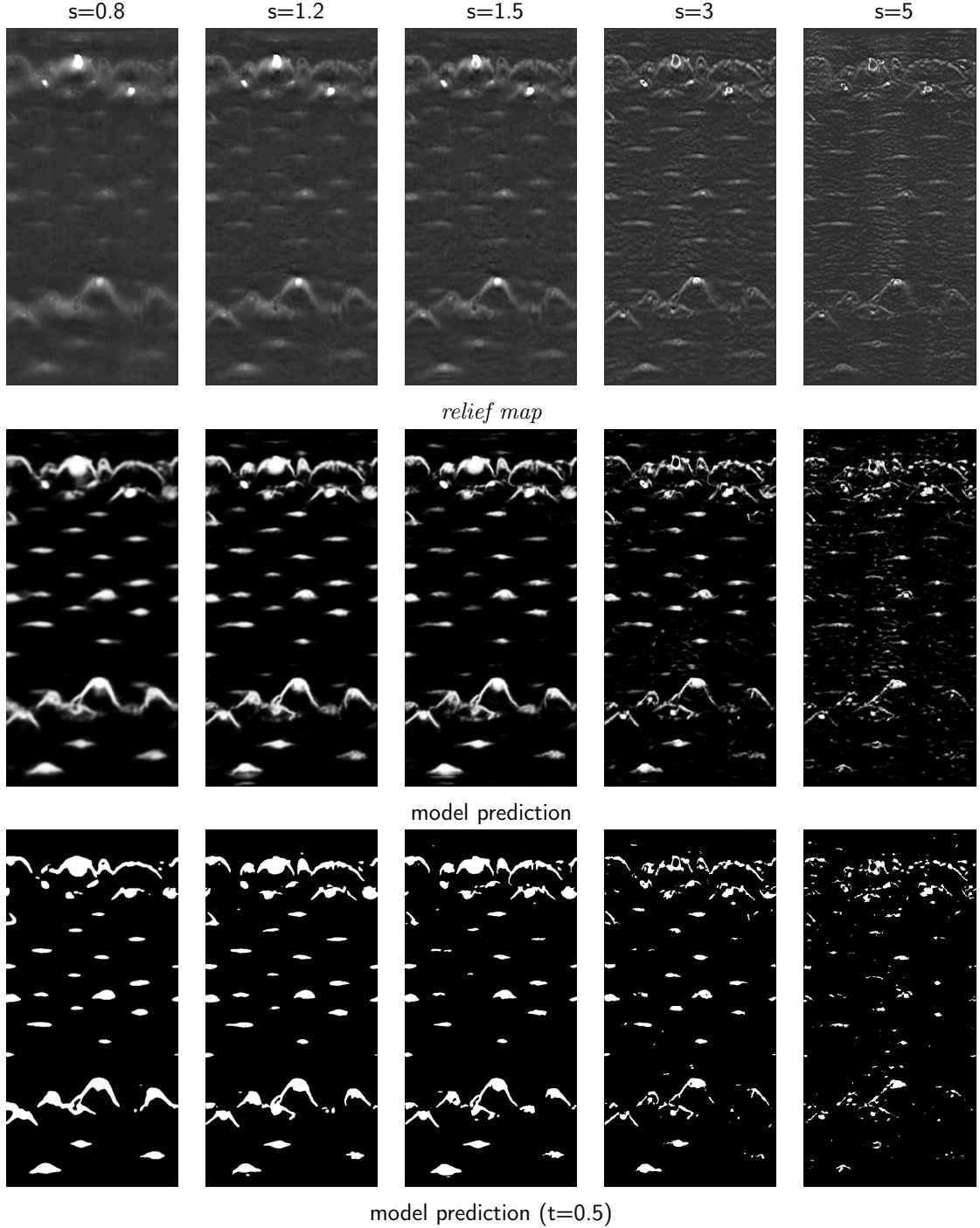


Figure 18: Our method segmentation on the example WildCherry1 at different scales.

In the future, we would like to work on the generation of a new type of map from the trunk meshes, in particular using the normals from face meshes. It will allow to represent the orientation of the face meshes in the image. We then will train a CNN to accumulate orientation and relief information to produce a segmentation. In addition, we plan to address the related objective of classifying the singularities according to their different types. Such features are interesting to get a finer estimation of the wood quality.

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Image Credits



images from the authors.

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