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► **To cite this version:**

Van-Tho Nguyen, Thiéry Constant, Bertrand Kerautret, Isabelle Debled-Rennesson, Francis Colin. A Machine-Learning Approach for Classifying Defects on Tree Trunks using Terrestrial LiDAR. *Computers and Electronics in Agriculture*, 2020, 171, pp.1-12. 10.1016/j.compag.2020.105332 . hal-02931277

HAL Id: hal-02931277

<https://hal.science/hal-02931277>

Submitted on 5 Sep 2020

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1 A Machine-Learning Approach for Classifying Defects
2 on Tree Trunks using Terrestrial LiDAR

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9 **Abstract**

Three-dimensional data are increasingly prevalent in forestry thanks to terrestrial LiDAR. This work assesses the feasibility for an automated recognition of the type of local defects present on the bark surface. These singularities are frequently external markers of inner defects affecting wood quality, and their type, size, and frequency are major components of grading rules. The proposed approach assigns previously detected abnormalities in the bark roughness to one of the defect types: branches, branch scars, epicormic shoots, burls, and smaller defects. Our machine learning approach is based on random forests using potential defects shape descriptors, including Hu invariant moments, dimensions, and species. The results of our experiments involving different French commercial species, oak, beech, fir, and pine showed that most defects were well classified with an average F_1 score of 0.86.

10 *Keywords:* roundwood quality, random forests, standing tree grading

11 **1. Introduction**

12 Grading standing trees and roundwoods is a critical task in a wood supply
13 chain before harvesting or processing in the wood industry (Fonseca, 2005).
14 This question is especially concerned by the general trend towards digitiza-
15 tion for forest wood-chain traceability, supply chain optimization, and trans-
16 formation (Pickens et al., 1997; Lin and Wang, 2012; Gardiner and Moore,
17 2014; Müller et al., 2019). After the overall shape characterization defining
18 material yield, and wood quality information coming from the cross-sectional
19 ends in the case of roundwood, wood quality is mainly assessed from singu-
20 larities of the bark surface. The occurrence of such singularities indicates
21 local variations of the material properties generally corresponding to de-
22 creased normal distribution of the clearwood properties and characteristics,
23 which detrimentally impact future products and their mechanical, physical
24 or aesthetical functions. Nevertheless, the resulting grade made by an expert
25 corresponds to a global assessment of the quality by taking many criteria
26 into account through grading rules. After the attribution of the grade, the
27 original causes are often forgotten.

28 Alternatives using X-ray computed tomography (CT) can be considered
29 as reference methods for such a characterization (Li et al., 1996; Zhu et al.,
30 1996; Aguilera et al., 2008; Colin et al., 2010b). On the one hand, CT can
31 achieve good accuracy for defect recognition (up to 95%; Li et al. (1996)),
32 detect the defects as small as 1 millimeter in diameter by manually placing
33 plot markers along the tracks of knot (Colin et al., 2010b), or automatically
34 detect knots (Longuetaud et al., 2012; Krähenbühl et al., 2012, 2016). In-
35 dustrial solutions are proposed by several companies (Microtec, 2019; Jörg

36 Elektronik GmbH, 2019). On the other hand, CT has its own limitations with
37 investment cost and the need to fell the tree and cut it into logs. Besides the
38 fact that grading rules are mainly defined from external observations where
39 bark is present, recent studies confirmed a strong correlation between inter-
40 nal and external defects (Thomas, 2009; Stängle et al., 2014; Racko, 2013;
41 Pyörälä et al., 2018) with coefficients of determination (R^2) greater than 0.6.
42 From these results and practices, the question arose as to the use of three-
43 dimensional (3D) technologies for describing the external envelope of trunks
44 or logs with the objective of detecting bark surface defects.

45 LiDAR (Light Detection and Ranging) can measure objects in three di-
46 mensions through a technique in which a laser beam is emitted and the
47 reflected light is received by a detector. The resulting product is a point
48 cloud that contains the three spatial dimensions (x, y and z coordinates) of
49 the scanned object. In forestry, terrestrial laser scanning (TLS) can provide
50 information about an individual tree or a plot (Dassot et al., 2011). A va-
51 riety of forestry applications have been developed in the last two decades.
52 In particular, a number of studies has taken advantage of the potential of
53 LiDAR for the replacement of conventional methods of measuring forest in-
54 ventory parameters, such as tree height, diameter at breast height (DBH,
55 trunk diameter measured at 1.3 m above ground level) (Hopkinson et al.,
56 2004; Simonse et al., 2003), stand density, stand basal area, and volume for
57 biomass assessment (Van Leeuwen and Nieuwenhuis, 2010; Yao et al., 2011;
58 Dassot et al., 2012; Astrup et al., 2014).

59 On standing trees, there have been attempts to estimate tree quality
60 criteria from TLS (Kankare et al., 2014; Blanchette et al., 2015), airborne

61 LiDAR (Maltamo et al., 2009; Luther et al., 2014; Kankare et al., 2014), or
62 both types of LiDAR (Van Leeuwen et al., 2011). The quality parameters
63 targeted in these works mainly concerned the overall shape of the timber:
64 ovality, curvature, taper, and the presence of branches. Research focused on
65 the detection of external defects are scarce (Schütt et al., 2004; Stängle et al.,
66 2014; Thomas et al., 2007; Kretschmer et al., 2013). Most of these studies
67 were dedicated to the detection of large and very obvious defects. Thomas
68 et al. (2007); Thomas and Thomas (2010) detected, on red oak and yellow
69 poplar, defects with a diameter greater than 7.5 cm and protruding by at
70 least 2.2 cm from the bark. Kretschmer et al. (2013) proposed an approach to
71 detect and manually measure the branch scars on Scots pine by highlighting
72 them on a 3D reconstruction of the bark surface: the bark surface is colored
73 based on the distance to a fitted cylinder surface corresponding to a trunk
74 part. The scars, with a diameter of at least 2 cm and protruding by at least
75 1.5 cm from the bark, were detected. Existing research on the automated
76 classification of defects on tree bark using TLS is even scarcer. Schütt et al.
77 (2004) presented a semi-automatic approach, based on a neural network, to
78 detect and classify wood defects using both range and intensity information
79 of TLS data.

80 In a previous work (Nguyen et al., 2016b), we successfully developed an
81 algorithm to detect the defects on trunks surface. Using a suitable spatial
82 resolution of the 3D data, the detection can segment potential defects with
83 a dimension as small as 1 cm and small protrusion on trunks of different tree
84 species. This important improvement was obtained from two major compo-
85 nents. First, the definition of the most relevant trunk centerline results from

86 a voting algorithm selecting the most frequent locations of the intersections
87 of the inward pointing normals to the surface. Secondly, the reference dis-
88 tance to the centerline is computed for each individual point by taking its
89 neighborhood into account. The computation of reference distance for each
90 individual point allows for more precisely detecting the abnormalities on the
91 bark than more global reference surface based on primitive fitting such as
92 cylinder (Schütt et al., 2004; Stängle et al., 2014; Kretschmer et al., 2013) or
93 circle (Thomas et al., 2007; Thomas and Thomas, 2010).

94 Returning to the main purpose of the work presented here, once potential
95 defects are detected, an automatic procedure must be able to assign them
96 to a defect type and to confirm their status. The main challenge in the
97 classification of these defects is to deal with the variability of their appear-
98 ance, even for the same type of defect. In the forestry domain, the defects
99 are often defined by the biological origin (Colin et al., 2010a) that leads to
100 a high intra-class variability and inter-class similarity. Figure 1 (c-f) and
101 (g-i) give examples of the intra-class variability between branch scars and
102 burls respectively. Inter-class similarity between an epicormic shoot and a
103 burl is shown in Figure 1 (b) and (g). Factors contributing to the intra-
104 class variability or inter-class similarity are the tree species, often linked to
105 the characteristics of its bark, the shape and the age of the defect and all
106 the history of its development in connection with the environment of the
107 tree. Facing this huge variability, a major difficulty is to build a representa-
108 tive database allowing the establishment of classification methods and their
109 testing especially in studying the feasibility of such an approach as in this
110 work. Several methods in the field of pattern recognition can be applied

111 to classify objects, such as neural networks (Bishop, 1995), support vector
112 machines (Cortes and Vapnik, 1995), random forests (Breiman, 2001), Bayes
113 classifier (Devroye et al., 1996), and deformable models (Terzopoulos and
114 Fleischer, 1988). Most approaches are based either on parametric models or
115 on machine-learning techniques. In the remote sensing domain, the machine-
116 learning supervised classifiers are widely used because they are more flexible
117 in handling the high variability in object appearance and are more robust
118 than model-based approaches (Niemeyer et al., 2014). In particular, random
119 forests are a supervised machine-learning method that is based on ensembles
120 of classification trees. Random forests exhibits many interesting properties,
121 such as high accuracy, robustness against over-fitting, noise or missing data
122 in the training set (Díaz-Uriarte and De Andres, 2006). Moreover, random
123 forests is a non-parametric method that does not require the information
124 on the distribution of data. These advantages make random forests a suc-
125 cessful classification method since its introduction by Breiman (2001). In
126 the domain of remote sensing, random forests were used in landcover clas-
127 sification or urban area classification from airborne LiDAR (Chehata et al.,
128 2009; Guo et al., 2011) or Landsat data (Yuan et al., 2005; Gislason et al.,
129 2006). In the forestry domain, random forests were used to accompany the
130 forest inventory, such as for biomass assessments (Mutanga et al., 2012), us-
131 ing airborne LiDAR. Othmani et al. (2013) used random forests to identify
132 the tree species from the analysis of tree bark pattern from the mesh derived
133 from TLS data. Random forests were used to assess the timber quality of
134 Scots pine by estimating tree properties, such as trunk diameters, tree height
135 and branch heights using the parameters computed from TLS data (Kankare

136 et al., 2014).

137 The main objective of this work is to classify the potential defects de-
138 tected on trunk surface by previously developed algorithms (Nguyen et al.,
139 2016b). The other objective is to evaluate the performance of a robust and
140 commonly used machine-learning algorithm, random forests, for the classifi-
141 cation of bark singularities. The targeted types of defects are branch, branch
142 scar, burl, and small defects including sphaeroblast, bud cluster, and picot.
143 These types were chosen to represent the existing diversity of defects; never-
144 theless, some were grouped because of the difficulty in distinguishing them
145 given their size or shape. We aimed to develop a method that works on the
146 common commercial tree species, including hardwood species like sessile oak
147 (*Quercus petraea* (Matt.) Liebl.), European beech (*Fagus sylvatica* L.), and
148 wild cherry tree (*Prunus avium* (L.) L.), or conifers such as silver fir (*Abies*
149 *alba* Mill.), Scots pine (*Pinus sylvestris* L.), and Norway spruce (*Picea abies*
150 (L.) H.Karst.). Here a special focus is given to the results concerning oak and
151 European beech two hardwood species that have very different bark rough-
152 ness, defect types and shapes. The first species has a furrowed bark and
153 its most common defect types are burl and picot. The second has smooth
154 bark and the most common defect type is branch scar with an eyebrow (or
155 "Chinese mustache") shape.

156 **2. Materials and Methods**

157 *2.1. Defects on trunk surface*

158 Several defects on the trunk surfaces can be caused by exogenous factors
159 depending on their environment, such as heat, frost, other trees, animals, and

160 human beings. Our study focused on the most frequent source of defects,
161 which arises from tree branching. Branching defects are the result of the
162 development and growth of the tree. Their scars are associated generally
163 with protruding regions that result from the inclusion of the defect by the
164 radial growth of the trunk. More precise definitions of what we considered
165 as a branching defect were as follows:

- 166 • A sequential branch was a branch that emerged after a winter's rest of
167 the original bud.
- 168 • An epicormic branch was a branch that emerged after several winters
169 from a latent bud.
- 170 • A branch scar was a track of a branch, either sequential or epicormic
171 that maintains when this branch has died and has been degraded.
172 Branch scars on hardwood were often referred to as bark distortions.
- 173 • A bud was a miniature leafy shoot protected by a covering of scales.
- 174 • A burl was a group of juxtapositional defects of one or more type, such
175 as bud, picot, branch or branch scar. By definition, a burl could have
176 a great variability in shape and size and composition.
- 177 • A bud cluster was a limited group of buds of less than six buds.
- 178 • A sphaeroblast was a bud whose base produces xylem that progressively
179 covers the apical meristem of the bud (mainly on beech) (Fink, 1999).
- 180 • A picot was a small branch with its apex naturally pruned. Picots are
181 defined and illustrated in Colin et al. (2010b).

182 Typical defects on trunk surface were represented in Figure 1. These
183 defects were characterized by a large intra-class variability in size and shape.
184 For instance, burls could range from a large bud cluster with at least six
185 buds to a very extended mass of buds, picots, short or long branches with a
186 diameter of several tens of centimeters.

187 The impact of defects on the wood quality depended on their type and
188 dimension. For defects of the same type, larger defects had a more important
189 impact than smaller ones. In general, the most penalizing defects were branch
190 scar, branch and burls. The impact of small defects such as bud cluster,
191 sphaeroblast and picot is small, but some had to be taken into account in
192 the highest quality class.

193 *2.2. Methodology*

194 The steps of our method are presented in Figure 2. After their acquisition,
195 the TLS data were preprocessed to obtain a smooth mesh corresponding to a
196 trunk portion. Next, the potential defects were detected by using a segmen-
197 tation algorithm, which is an improved version of the previously published
198 work (Nguyen et al., 2016b) and is summarized in section 2.5. Then, the po-
199 tential defects were classified into defect types using trained random forests.
200 Finally, the results were visualized by various colors on the mesh according
201 to the defect type. The classification was validated by comparing the results
202 with the ground-truth labels classified by an expert on the trunks before
203 the TLS scans were carried out. Two methods were used by the expert to
204 mark the defect type. The first method used small distinctive shape pinned
205 in the vicinity of the defect. Thus, the defect type was recognized in the
206 reconstruction of trunk surface. The second method measured the coordi-

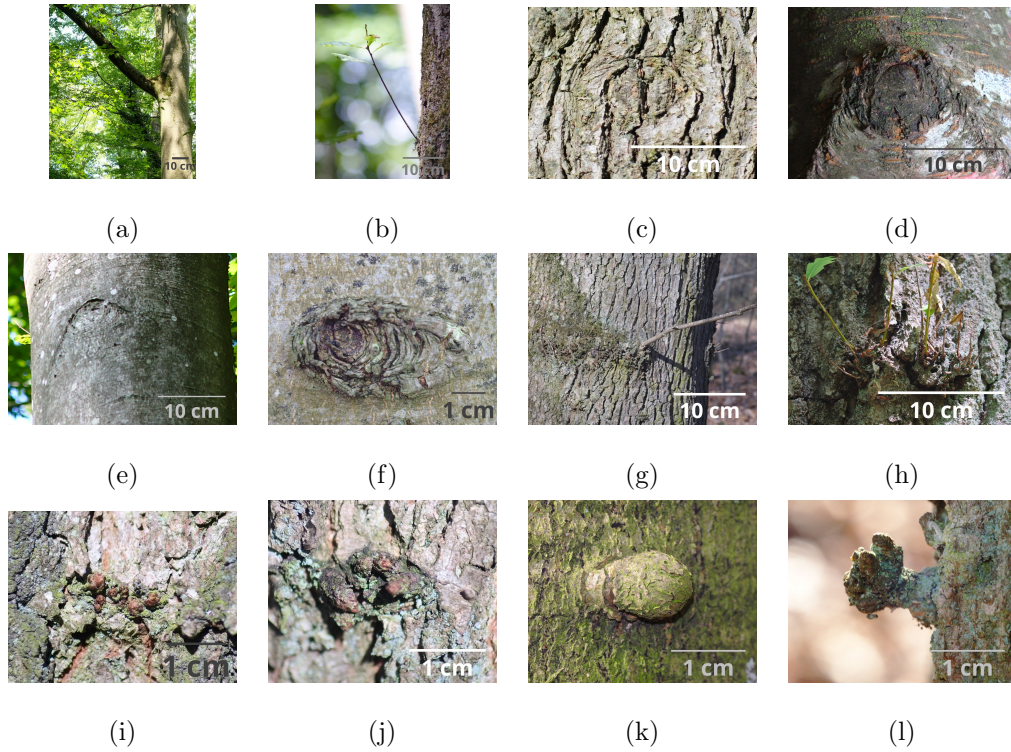


Figure 1: Some illustrations of the defect types considered in this study. (a, b) branches: sequential branch (a), and epicormic shoot (b); (c-f) branch scars: on oak (c), on wild cherry (d), on beech (e), and on beech (f); (g, h) burl: consisting of buds and an epicormic shoot (g), buds and short epicormic shoots (h), and buds (i); small defects: (j) bud cluster, (k) sphaeroblast, and (l) picot.

207 nates of the defects by a local coordinate (l, z) system on the trunk with l
 208 the position along a longitudinal axis Oz and l the signed arc length between
 209 the reference axis and the defect center. Two ping-pong balls were used to
 210 define the axis. A dedicated software was developed to recover the same
 211 coordinate system on the reconstruction of trunk surface, which allowed for
 212 measuring the defect coordinates and comparing with the ground truth. The

213 ground truth contained all of the defects with a diameter equal or greater
214 than 0.5 centimeters and from 0.5 to 2 meters or 5 meters depending on the
215 distribution of defects.

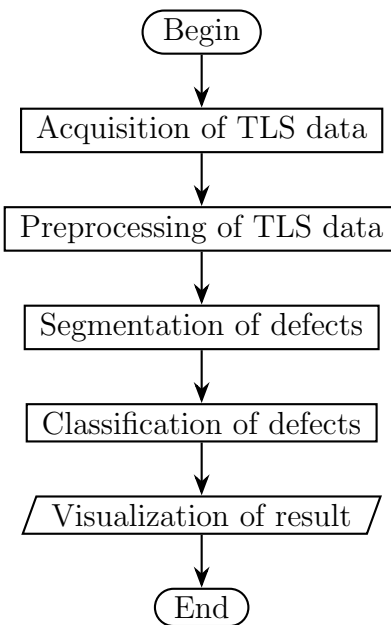


Figure 2: Overview of the processing flow for classifying the surface defects onto a trunk.

216 2.3. Acquisition of TLS data

217 The tree trunks exhibiting different defects were measured with a Faro Fo-
218 cus 3D X130 laser scanner in the Champenoux and Haye forests in the Grand-
219 Est region of France. To detect small defects, we chose a high-resolution set-
220 ting and put the scanner close to the trunk. The utilized resolution was one
221 half of the maximum value and the distance from the scanner to the trunk
222 was approximately 3-4 meters. With this setting, the angular resolution of
223 the scan was 0.018° in both horizontal and vertical directions, and the result-
224 ing distance between two neighboring 3D points on the trunk surface in the

225 point cloud was around 1 millimeter. Such settings ensured a high-quality de-
226 scription of the defects limiting the laser beam inclination resulting from the
227 defect height and the distance to the tree. The trees were sampled according
228 to several criteria. Among the main commercial species, selected trees must
229 have a sufficiently large diameter (see Table 1) and represent a variability in
230 bark roughness, which depends on the species and the age of the trees. In
231 agreement with these criteria, we scanned 26 trees: nine sessile oaks, eight
232 European beeches, three wild cherries, two Scots pines, three silver firs, and
233 one Norway spruce. These scans were divided into 2 sets. One was used to
234 train the random forests and another was used to test the method efficiency
235 (Table 1). The training set contained 425 defects from 16 trees and the test
236 set contained 183 defects from 10 trees.

237 During this acquisition step, the objective was to maximize the number
238 and type of defects per scan; thus, trunks were either scanned entirely with
239 four scans from suitable points of view or partially with one or two scans on
240 just one side. If the trunk was scanned from multiple points of view, the scans
241 were merged into a single file per tree to recover the 3D view of the trunk.
242 The registration was performed by the standard procedure available in the
243 FARO SCENE software (Faro Technologies Inc., Lake Mary, FL), through
244 the use of spheres.

245 *2.4. Preprocessing of TLS data*

246 LiDAR data are generally noisy, and the first processing step aimed to
247 manage noise for enhancing the recognition rate. It included the reduction
248 of noise and the smoothing of the trunk surface. Noise reduction is a difficult
249 and complex process, due to different noise patterns from scan to scan. It

Table 1: Number and attributes of the sample trees.

| Species | Number of trees | | Range of diameters |
|-------------|-----------------|---------|-----------------------|
| | Training | Testing | at breast height (cm) |
| Oak | 6 | 3 | 35 - 76 |
| Beech | 5 | 3 | 30 - 57 |
| Wild cherry | 2 | 1 | 22 - 33 |
| Pine | 1 | 1 | 34 - 57 |
| Fir | 2 | 1 | 23 - 45 |
| Spruce | 0 | 1 | 19 |
| Total | 16 | 10 | |

250 depends on the condition of the scanning environment and also the charac-
 251 teristics of the trees. For example, we observed that when the trunk had
 252 branches or small epicormic shoots, there was much of noise caused by the
 253 multiple interceptions of the same laser beam by several branches and the
 254 bark. This is the situation when a laser beam hits both the contour of the
 255 branch and the bark resulting in a ghost point, with no reality, between the
 256 branch and the bark (Figure 3 (a)). We observed that the point density in
 257 noisy regions was often lower than in the relevant data regions. Thus, we
 258 proposed a simple approach to remove noise by clustering the point cloud by
 259 Euclidean distance with the idea that relevant data points are in the largest
 260 cluster where the point density is highest. The choice of the threshold on the
 261 minimal distance between clusters is critical. If the threshold is too small,
 262 there is a risk that the relevant data would be removed, especially in the high
 263 part of the trunk where the resolution is lower. After testing different values,

264 we set the threshold to 5 millimeters, which gave the best visual results for
265 our scanning settings.

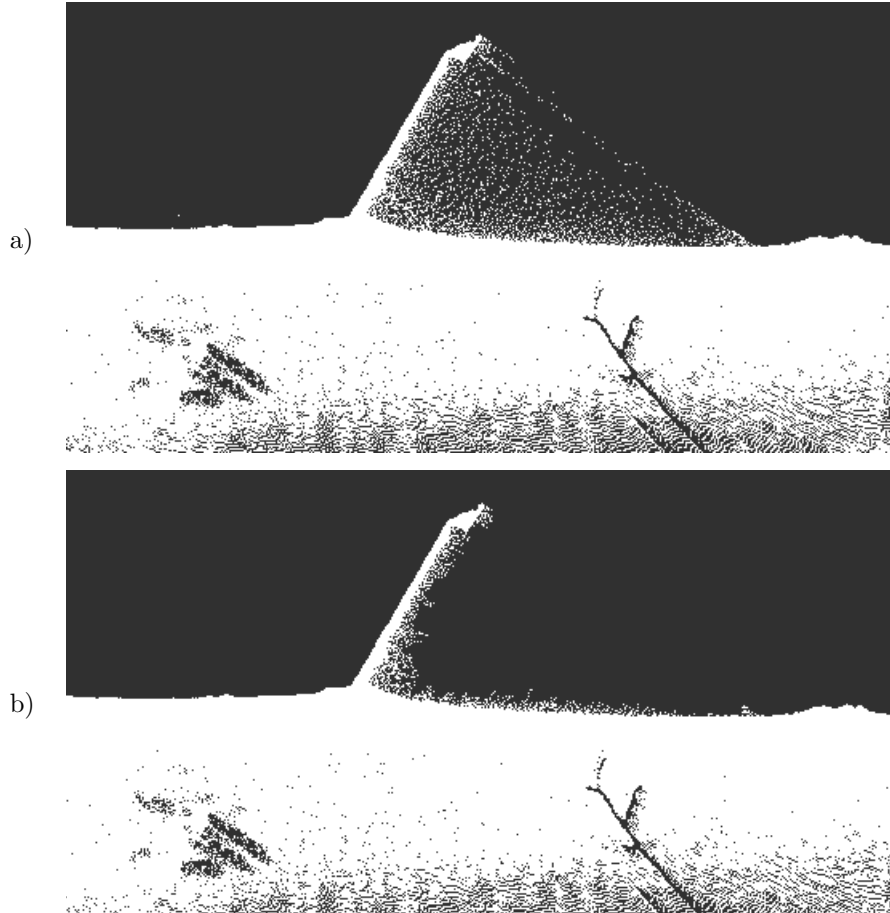


Figure 3: Noise processing for a wild cherry trunk. Point cloud before (a) and after (b) noise reduction process that only keeps the biggest cluster; the minimal distance between two clusters is 5 millimeters.

266 Due to the nature of a laser scan, the raw point cloud contains a cer-
267 tain level of error. For example, the utilized scanner had a ranging er-
268 ror of ± 2 millimeters at 10 meters. The smoothing step was performed

269 to reduce surface roughness caused by ranging uncertainty. However, the
270 smoothing intensity was limited to maintain the bark roughness or defect
271 shapes. The following steps were performed for smoothing and creating
272 a mesh from the trunk point cloud using the Graphite software (https://gforge.inria.fr/frs/?group_id=1465):
273

- 274 1. Smooth the point cloud (Lévy and Bonneel, 2013) using only one it-
275 eration with 30 neighbors. Only one iteration was used because with
276 more iterations the smoothing process may erase defects with a weak
277 relief.
- 278 2. Reconstruct the trunk surface (Boltcheva and Lévy, 2017) with the
279 normal vector computed from 30 neighbors and the maximum distance
280 used to connect neighbors of 5 millimeters. The radius value was chosen
281 to be greater than the between-point distance in the point cloud but
282 not too large to prevent the creation of wrong edges.
- 283 3. Smooth the created mesh by using the remesh smooth function (Lévy
284 and Bonneel, 2013). The used parameter was the number of points
285 similar to the one of the original point cloud.

286 *2.5. Segmentation of defects*

287 Our strategy to classify the defects on trunk surface was first to detect all
288 potentially defective areas using a segmentation algorithm. The algorithm is
289 an enhanced version of our previously published one (Nguyen et al., 2016b)
290 that focuses on defects with little protuberance from tree bark. In this study,
291 we proposed a preliminary step for segmenting tree branches. The motivation
292 for developing this approach came from the existing links between a defect

293 present in the woody part and the impact of that defect on the bark surface,
 294 expressed by a structured, and often protruding, irregularity. To detect these
 295 irregularities, we defined the centerline of the trunk as a reference. In the
 296 evaluation of the algorithm presented in Nguyen et al. (2016b), the presence
 297 of branches was identified as an inconvenience for detecting smaller defects
 298 in a branch vicinity. Thus, in this work, the branches were first segmented
 299 by an algorithm that separates the points into two disjointed sets (illustrated
 300 in Figure 4): (1) set T contains closer points to the trunk surface, and (2)
 301 set B contains the branches according to the following algorithm.

- 302 • Estimation of the trunk radius r_m , using the mode of the distance to
 303 the centerline of all points in the point cloud.
- 304 • Division of the point cloud volume into slices with a thickness of l mil-
 305 limeter, following the centerline direction. Each slice was then divided
 306 into angular sectors with an angle of $\frac{l}{r_m}$ radian. The value of l should
 307 be greater than the diameter of the largest branch. In our experiment,
 308 the l parameter was set to values between 50 and 100 millimeters.
- 309 • For each angular sector, the nearest point to the center of the trunk
 310 was added to set T , and the other points of the portion were added to
 311 set B .
- 312 • For each point P in set T , we found subset S of set B , such as the
 313 distance between point $S_i \in S$ and P was less than or equal to $\sqrt{2}l$,
 314 and we moved them in set T . This algorithm assured that no point
 315 on trunk surface left on the branches set B by accepting a branch part
 316 with a length of $\sqrt{2}l$ on the trunk set T .

317 After the branch segmentation, the original method (Nguyen et al., 2016b)
 318 was applied to set T as follows. (i) For each point P in set T , we estimated
 319 a reference point \hat{P} from a linear regression linking the radius variation to
 320 longitudinal positions on a patch of neighboring points of P . (ii) The defect
 321 points were detected by thresholding the difference between the distance from
 322 P and \hat{P} , denoted as (δ) . (iii) The threshold was automatically computed
 323 on the histogram of δ using the Rosin's method (Rosin, 2001). Then, the
 324 detected defect points were merged with set B containing the branches to
 325 form a set of defect points D . The different potential defects were obtained
 326 by clustering the defect points D by using Euclidean distance.

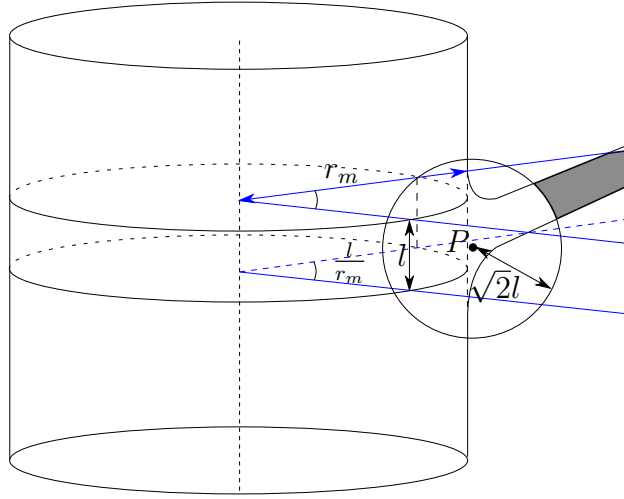


Figure 4: Illustration of the branch segmentation: the angular sector is defined by the volume inside planes formed by blue lines. The points in this angular sector that had a distance to P less than or equal to $\sqrt{2}l$ were moved to the set of trunk points (T). The set of branch points (B) is in solid grey color.

327 *2.6. Classification of defects*

328 *2.6.1. The random forests classifier*

329 The random forests (Breiman, 2001) classifier is an ensemble classifier
330 that aggregates a set of classification and regression trees (CARTs) (Breiman
331 et al., 1984) to make a prediction. In the training step, all trees were built
332 with the same parameters but on different subsets of the training samples.
333 These subsets were generated from the training samples by a bootstrap sam-
334 pling, which randomly selected the same number of vectors from the original
335 set. The remaining "out-of-bag" (OOB) was used to compute the estimation
336 error, which is known as the OOB error. Unlike CART, random forests does
337 not consider all variables at each node to determine the best split threshold
338 but a random subset of variables of the feature vector and the trees are built
339 without pruning. The cardinality of the subset is an input parameter.

340 Another important parameter of the random forests classifier is the num-
341 ber of trees, which must be sufficiently large to capture the full variability
342 of the training data and yields good classification accuracy. One of the ad-
343 vantages of the random forests classifier is that it does not overfit when
344 increasing the number of trees at the expense of slower running time. In the
345 classification step, random forests tested the feature vector, describing the
346 new object with each tree in the forest. Each tree made a classification, or
347 in other words, gave a vote for a class. The random forests classifier chose
348 the class on which the majority of trees voted.

349 As mentioned above, the number of trees in the forest (*nbTrees*) and the
350 number of variables (*nbVariables*) used to select and test for the best split
351 when growing the trees are two important input parameters needed to train

352 the random forests classifier. The OOB error can be used to find the optimal
353 value for these parameters. We ran an experiment with the *nbTrees* from
354 100 to 5,000 and the *nbVariables* from 1 to the number of variables of the
355 feature vector. For each value of *nbVariables*, we could find the minimum
356 value of *nbTrees*, which gave the minimum OOB error.

357 The random forests has been implemented in a number of free and open
358 source libraries. In this study, we used the implementation in OpenCV-
359 3.3 (Bradski, 2000). The advantage of OpenCV is its compatibility with
360 the implementation of our algorithms in C++ programming language. The
361 source code and sample data are available at the following GitHub repository:
362 <https://github.com/vanthonguyen/trunkdefectclassification>

363 2.6.2. Feature vector

364 In this step, we used the defects detected by our segmentation algorithm
365 and constructed the feature vector based on our expertise on the defects.
366 Before computing the features, the point cloud of the defect was converted
367 from Cartesian coordinate system to a custom coordinate system $\{l, z, d\}$,
368 where l is the arc length computed from angle between the point and the
369 plane Oxz and the distance from the point to the centerline, z is the height,
370 and d is the difference between the distance and the reference distance from
371 the point to the centerline (the distance between P and \hat{P} as presented in
372 section 2.5). This conversion allowed us to measure the defect diameter along
373 the curved surface of the trunk similar to a manual measurement. To reduce
374 the inhomogeneity of point clouds due to the superimposition of data coming
375 from several points of view or the non-uniform by TLS, the feature vector
376 was computed from a subsampled point cloud. The subsampled point cloud

377 latter was computed by keeping only the closest point to the center of each
 378 voxel of a regular voxel grid of the defect point cloud. The voxel size was
 379 chosen by the average point spacing, which was 3 mm in our study. The
 380 following features were used:

- 381 1. Species: s .
- 382 2. Ratio between the number of points of the defect and the volume of its
 383 bounding box: c (equation 1)
- 384 3. Defect arc length: $w = l_{max} - l_{min}$.
- 385 4. Ratio between w and defect height: $\frac{w}{h}$ where h equals $z_{max} - z_{min}$.
- 386 5. Ratio between w and maximum of d : $\frac{w}{d_{max}}$.
- 387 6. Mean of difference between the distance from P and \hat{P} for all points P
 388 of the defect: \bar{d} .
- 389 7. Standard deviation of the difference between the distance from P and
 390 \hat{P} for all points P of the defect: σ_d .
- 391 8. Hu moment invariants: $I_1, I_2, I_3, I_4, I_5, I_6, I_7$ (see equations 4–10).
- 392 9. Ratio between the eigenvalue λ_1 and the eigenvalue λ_3 : $\frac{\lambda_1}{\lambda_3}$.
- 393 10. Ratio between the eigenvalue λ_2 and the eigenvalue λ_3 : $\frac{\lambda_2}{\lambda_3}$.
- 394 11. Angle between the eigenvector \vec{v}_3 and the trunk axis at the height of
 395 defect: α .

396 where λ_1 is the eigenvalue associated with the eigenvector \vec{v}_1 of the defect
 397 having the smallest angle, with the radial vector of the trunk at the center
 398 of the intersection between the defect and the trunk. λ_2 is the eigenvalue
 399 associated with the eigenvector \vec{v}_2 of the defect having the smallest angle with
 400 the tangential vector of the trunk at the center of the intersection between

401 the defect and the trunk. λ_3 is the eigenvalue associated with the eigenvector
402 \vec{v}_3 of the defect having the smallest angle with the trunk axis at the height
403 of defect.

404 The species was an important variable because each one had a specific
405 bark roughness and a set of defects. For example, oak had burls but does
406 not had sphaeroblast, which was conversely related to beech. In addition,
407 for the same defect type, its shape could differ from one species to another.
408 For example, a branch scar on oak and on beech was very different.

409 Another relevant variable was the ratio between the number of points of
410 the defect and the volume of its bounding box, which measured the com-
411 pactness of the defect in the $\{l, z, d\}$ coordinate system equation (1). This
412 feature could discriminate a flat defect and a significantly protruding defect.

$$c = \frac{\text{number of points}}{(l_{max} - l_{min})(z_{max} - z_{min})(d_{max} - d_{min})} \quad (1)$$

413 By using our expertise in the domain, the dimension was an important
414 criterion to classify defects, in particular small defects such as small burl and
415 bud cluster. For that reason, we included the arc length w as a feature. The
416 ratio $\frac{w}{h}$ allowed us to distinguish between a branch scar and a bark zone,
417 which had a roughness higher than the local average on oak tree because the
418 branch scars often have width greater than height and bark zones have width
419 smaller than height. The ratio $\frac{w}{d_{max}}$ helped to distinguish a flat object, such
420 as bark portion, branch scar and a more protruding one such as sphaeroblast
421 and picot. The mean and standard deviation of d were also included in the
422 feature vector because they help to distinguish between a branch scar and a
423 burl composed only of buds.

424 The Hu moment invariants (Hu, 1962) had good characteristics for the
 425 object recognition because they were invariant with respect to translation,
 426 scale, and rotation. The Hu moment invariants $\{I_1, \dots, I_7\}$ were computed
 427 from the normalized central moments nu_{ij} of orders $(i + j) = 2$ and 3 (see
 428 equations (3)–(10)).

$$mu_{ij} = \sum_{z,l} (z - \bar{z})^i (l - \bar{l})^j d \quad (2)$$

$$nu_{ij} = \frac{mu_{ij}}{mu_{00}^{(i+j)/2+1}} \quad (3)$$

$$I_1 = nu_{20} + nu_{02} \quad (4)$$

$$I_2 = (nu_{20} - nu_{02})^2 + 4nu_{11}^2 \quad (5)$$

$$I_3 = (nu_{30} - 3nu_{12})^2 + (3nu_{21} - nu_{03})^2 \quad (6)$$

$$I_4 = (nu_{30} + nu_{12})^2 + (nu_{21} + nu_{03})^2 \quad (7)$$

$$I_5 = (nu_{30} - 3nu_{12})(nu_{30} + nu_{12})[(nu_{30} + nu_{12})^2 - 3(nu_{21} + nu_{03})^2] + \quad (8)$$

$$(3nu_{21} - nu_{03})(nu_{21} + nu_{03})[3(nu_{30} + nu_{12})^2 - (nu_{21} + nu_{03})^2]$$

$$I_6 = (nu_{20} - nu_{02})[(nu_{30} + nu_{12})^2 - (nu_{21} + nu_{03})^2] + 4nu_{11}(nu_{30} + nu_{12})(nu_{21} + nu_{03}) \quad (9)$$

$$I_7 = (3nu_{21} - nu_{03})(nu_{30} + nu_{12})[(nu_{30} + nu_{12})^2 - 3(nu_{21} + nu_{03})^2] + \quad (10)$$

$$(3nu_{12} - nu_{30})(nu_{21} + nu_{03})[3(nu_{30} + nu_{12})^2 - (nu_{21} + nu_{03})^2]$$

429 The eigenvectors and eigenvalues of the defect were computed from a
 430 principal component analysis (PCA) (Wold et al., 1987), which could be
 431 useful for distinguishing between the defect with a long axis (branch) and
 432 the flatter ones. Furthermore, because of the small number of branches in our

433 dataset, we did not distinguish between sequential branches and epicormic
434 ones. Nevertheless, the angle between the eigenvector \vec{v}_1 of defect and the
435 trunk axis could be used to classify these types of branch on beech, oak and
436 fir, as epicormic branches were quasi-perpendicular to the trunk axis, while
437 sequential branches were more fastigiated.

438 *2.6.3. Construction of the training dataset*

439 We used both manually segmented and automatically segmented defects
440 to train the random forests. The manual segmentation was done by using
441 a home-made software (DGTalTools-Contrib), based on the library DGTal
442 (DGTal). The software allowed us to select the faces on the mesh to define
443 the footprints of the defects (Figure 5). Each defect was then saved in a
444 separate file and used for training the random forests. We also trained the
445 random forests using the results of our segmentation algorithm, along with
446 the verification given by the shape of paper labels set in the vicinity of the
447 defects and identifiable in the scan. Bark (no-defect) class was introduced
448 even though it is not a defect type; they were bark zones with a roughness
449 higher than the local average. These bark zones are often miss detected
450 as a defect by the segmentation algorithm. This is concordant with our
451 approach as the detection step was built to provide all potential zones of
452 defects assuming the risk of false positive that could be eliminated in the
453 classification step. The training database includes the following classes and
454 the number of defects of each class is summarized in Table 2:

- 455 1. Branch, including sequential branch and epicormic branch.
- 456 2. Branch scar.
- 457 3. Burl.

458 4. Small defects, including picot, sphaeroblast, bud and bud cluster.

459 5. Bark.

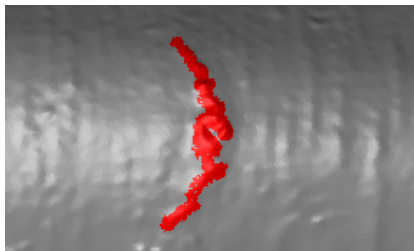


Figure 5: Manual segmentation of a defect

Table 2: Summary of the defects and barks encountered in the training set.

| Species | Branch | Branch scar | Burl | Small defects | Bark |
|-------------|--------|-------------|------|---------------|------|
| Oak | 7 | 3 | 159 | 63 | 116 |
| Beech | 34 | 51 | 26 | 20 | 2 |
| Wild Cherry | 15 | 5 | 0 | 0 | 0 |
| Pine | 0 | 4 | 0 | 0 | 0 |
| Fir | 0 | 38 | 0 | 0 | 10 |
| Total | 56 | 101 | 185 | 83 | 128 |

460 *2.6.4. Performance evaluation criteria*

461 To evaluate the performance of the classification algorithm, we used the
462 F-measure, a performance measurement, that is frequently used for classi-
463 fication problems. The F-measure is the harmonic mean of precision (PR)
464 and recall (RE). We used the F_1 score, mixing both with equal weights on
465 PR and RE . The precision PR is the number of correctly classified positive

466 defects divided by the number of defects labeled by the system as positive
 467 (equation (11)). The recall is the number of correctly classified positive de-
 468 fects divided by the number of positive defects in the data (equation (12)).
 469 On a binary classification problem, the F_1 is defined by equation (equation
 470 (13)).

$$PR = \frac{TP}{TP + FP} \quad (11)$$

$$RE = \frac{TP}{TP + FN} \quad (12)$$

471 where TP, FP, FN are true positive, false positive and false negative respec-
 472 tively. Their definition is as follows:

- 473 • TP is the number of actual defects correctly classified as defect.
- 474 • FP is the number of non-defects incorrectly classified as defect.
- 475 • FN is the number of actual defects incorrectly classified as non-defect.

$$F_1 = 2 \frac{PR \cdot RE}{PR + RE} \quad (13)$$

476 For a multi-class classification problem, the F-measure must be extended
 477 from the binary classification by an average of the F-measure of each class.
 478 There are two approaches (Manning et al., 2008). One approach is the macro-
 479 averaged F-measure (equation (14)), which is the unweighted mean of F-
 480 measure for each label. The other is the micro-averaged F-measure (equation
 481 (15)), which considers predictions from all instances together and calculate

482 the F-measure across all labels. Arithmetically, the micro-averaging favors
 483 bigger classes.

$$F_{m1} = \frac{\sum_{i=1}^n F_{1i}}{n} \quad (14)$$

$$F_{\mu 1} = 2 \frac{PR_{\mu} \cdot RE_{\mu}}{PR_{\mu} + RE_{\mu}} \quad (15)$$

$$PR_{\mu} = \frac{\sum_{i=1}^n TP_i}{\sum_{i=1}^n (TP_i + FP_i)} \quad (16)$$

$$RE_{\mu} = \frac{\sum_{i=1}^n TP_i}{\sum_{i=1}^n (TP_i + FN_i)} \quad (17)$$

484 where n is the number of classes.

485 We also used the confusion matrix (Provost and Kohavi, 1998) to evaluate
 486 the performance for a more detailed analysis of the misclassification between
 487 classes.

488 3. Results

489 In this section, we present the results of the segmentation algorithm fol-
 490 lowed by the results of the classification algorithm in comparison with the
 491 ground-truth data. We first present a global analysis of the performance
 492 related to exhaustiveness independently of the defect type focused on the
 493 differences coming from tree species. Then, the analysis of the results fo-
 494 cuses on defect types independently of the species which are nevertheless
 495 considered in the discussion.

496 Table 3 shows the results of the segmentation algorithm for each individ-
497 ual tree in the test database in terms of defect detection. We can see that
498 the segmentation algorithm detected almost all of the defects, with 179 de-
499 tected out of 183 (97.8%) in total. However, the number of false positives was
500 very high (765), which will then be removed by the classification algorithm
501 through a refined analysis of each detected areas. Moreover, Table 3 also
502 shows that these false positives were mostly removed by the classification
503 algorithm at the expense of some defects lost. The classification algorithm
504 removed not only 694 (90.7%) false positives but also 28 (15.3%) actual de-
505 fects.

506 We also observed that the segmentation algorithm produced more false
507 positives on trees with furrowed barks, such as oak and pine, than on trees
508 with smooth barks, such as beech and wild cherry. By contrast, the classi-
509 fication algorithm removed the false positives more efficiently on trees with
510 furrowed bark than on trees with smooth-bark. For example, in Table 3, we
511 can see that on pine the number of false positives from the segmentation and
512 classification are 105 and 2 respectively while on Beech 2 these numbers are
513 70 and 12, respectively. The difference is illustrated in Figure 6.

Table 3: Results of the segmentation (seg.) and classification (cla.) steps compared with the observed defects.

| Tree name | Observed | True positive | | False positive | | False negative | |
|-------------|----------|---------------|------|----------------|------|----------------|------|
| | | Seg. | Cla. | Seg. | Cla. | Seg. | Cla. |
| Oak 1 | 8 | 8 | 8 | 9 | 0 | 0 | 0 |
| Oak 2 | 25 | 24 | 19 | 147 | 7 | 1 | 6 |
| Oak 3 | 24 | 23 | 20 | 79 | 7 | 1 | 4 |
| Beech 1 | 30 | 30 | 24 | 55 | 19 | 1 | 6 |
| Beech 2 | 29 | 29 | 21 | 70 | 12 | 0 | 8 |
| Beech 3 | 24 | 22 | 18 | 47 | 14 | 2 | 6 |
| Wild Cherry | 8 | 8 | 8 | 10 | 0 | 0 | 0 |
| Pine | 4 | 4 | 4 | 105 | 2 | 0 | 0 |
| Fir | 14 | 14 | 14 | 129 | 8 | 0 | 0 |
| Spruce | 17 | 17 | 15 | 114 | 2 | 0 | 4 |
| Total | 183 | 179 | 151 | 765 | 71 | 5 | 34 |

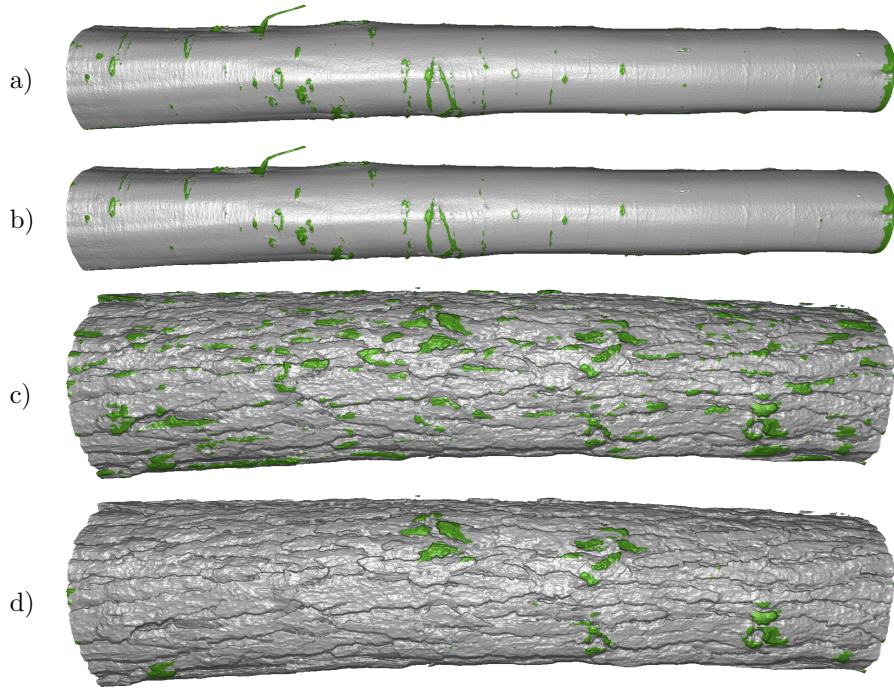


Figure 6: Defects detected by the segmentation algorithm (a, c) and refinement by the classification algorithm (b, d) for two logs: Beech 2 (a, b) and Pine (c, d).

514 Concerning the performance according to defect types, Figure 7 illustrates
 515 classification results by coloring the mesh in agreement with the defect type.

516 Table 4 shows the performance criteria by defect types resulting from the
 517 classification. The overall macro- and micro-averaged scores were 0.86 and
 518 0.73, respectively. However, the algorithm did not perform equally well on all
 519 classes of defect. The branch had the best F_1 score of 0.89, followed by the
 520 burl with an F_1 score of 0.76. The algorithm performed less well on branch
 521 scar and the small defect types with F_1 scores of 0.61 and 0.46, respectively.

522 For allowing a better understanding of the differences, Figure 8 represents
 523 the confusion matrix of the classification result. The matrix shows the match-

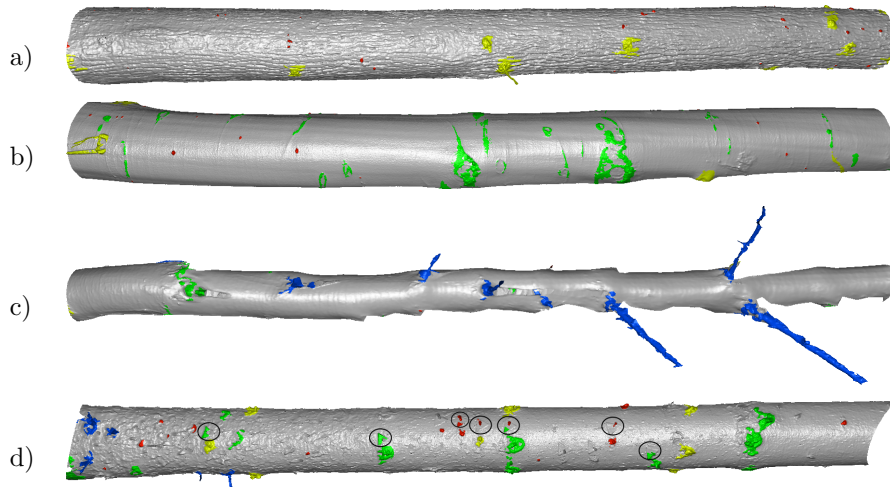


Figure 7: Examples of the classification results on the mesh of Oak 3 (a), Beech 1 (b), Wild cherry 3 (c), and Spruce (d). **Blue** is **Branch** type including both sequential and epicormic branches, **Green** is **Branch scar**, **Yellow** is **Burl**, **Red** is **Small defect** including bud cluster, sphaeroblast and picot. On the mesh of the Spruce, the detected defects (circled) are the paper marks and pushpins that were used by the expert to mark the defect type before the scan was carried out. These false positives were ignored in our evaluation.

524 ing between predicted and observed defect types and allows a finer analysis
 525 of the differences. We can see that one branch was classified as branch scar.
 526 A more detailed analysis showed that it was a short dead stub branch of a
 527 wild cherry (the large green region in Figure 7 (c)). Another branch was
 528 classified as a burl because an epicormic branch is often originated from a
 529 small burl, and the distinction by the algorithm is difficult in young develop-
 530 ment stages. While the recall of the algorithm on the branch scar was very
 531 high (0.84), the precision was not as good (0.48) because there were 49 bark
 532 portions recognized as branch scar while there were 69 branch scars in total.
 533 Some burls were confounded with the bark portions and small defects be-

Table 4: Precision, recall and F_1 score of the different defect types

| Defect type | Precision | Recall | F_1 |
|--------------------|------------------|---------------|-------------------------|
| Branch | 1.00 | 0.80 | 0.89 |
| Branch scar | 0.48 | 0.84 | 0.61 |
| Burl | 0.73 | 0.81 | 0.76 |
| Small defect | 0.56 | 0.39 | 0.46 |
| Bark | 0.95 | 0.90 | 0.93 |
| Beech (micro avg.) | 0.70 | 0.70 | 0.70 |
| Beech (macro avg.) | 0.70 | 0.70 | 0.70 |
| Oak (micro avg.) | 0.90 | 0.90 | 0.90 |
| Oak (macro avg.) | 0.66 | 0.68 | 0.67 |
| All (micro avg.) | 0.86 | 0.86 | 0.86 |
| All (macro avg.) | 0.75 | 0.74 | 0.73 |

534 cause a burl consisting of only buds may have a similar look to a small defect
535 (see Figure 1 (i) and (j)) or a bark portion since both are quite flat. The
536 confusion matrix shows that the small defects were often confounded with
537 bark portions and branch scars. It is to be noted that the number of bark
538 portions miss-classified as small defects was 15 and the number of small de-
539 fects miss-classified as bark portions was 16. There was only one branch scar
540 miss-classified as small defect but 11 small defects miss-classified as branch
541 scars.

542 Although no spruce data were used to train the random forests, the predic-
543 tions on this spruce (Figure 7 (d)) were good, as 15 out of 18 were detected.
544 However, two branch scars were detected as small defects and two branch

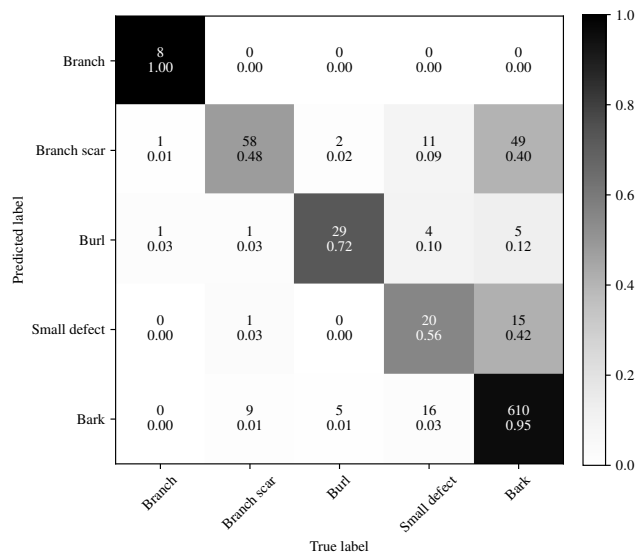


Figure 8: Confusion matrix with the absolute value and normalized value (precision). The color of cells is a function of normalized value.

545 scars were detected as burls.

546 4. Discussion

547 4.1. Defect detection

548 In summary, our algorithms had a very good performance in defect de-
 549 tection, even with the small defects corresponding to a slight modification of
 550 the bark roughness. These good results are both due to the robust estima-
 551 tion of the trunk centerline, and the fitting on a local longitudinal patch, of
 552 the regular radius variation, allowing for the calculation a local reference dis-
 553 tance. Our approach outperforms the detection based on a radius resulting
 554 from the fitting of geometrical primitives such as circle or cylinders proposed
 555 in other works (Thomas et al., 2007; Kretschmer et al., 2013) especially for
 556 cross-sections with less circular shape as already discussed in Nguyen et al.

557 (2016b). It is clear that several factors can impact the detection, such as
558 scan resolution and quality and missing data resulting from occlusion. Our
559 algorithm can detect small defects such as picot which often have a diameter
560 between 0.5 centimeter and 1 centimeter, thus outperforming all previous
561 works with size ranging from 7.5 centimeters (Thomas et al., 2007) to 2.0
562 centimeters (Kretschmer et al., 2013). Moreover, Kretschmer et al. (2013)
563 only focused on the branch scars and their method was not automatic.

564 Because of their shapes, French and North American foresters have named
565 large branch scars of beech and wild cherry trees "Chinese mustache" (or
566 eyebrow). It often covers a large peripheral area, and the two parts of the
567 mustache are often thin. This may result in an over-segmentation (Figure 9
568 (a)). Two or more large defects can also be close enough to form a large shape.
569 Although the human eye will dissociate the large shape as multiple separated
570 defects, the algorithm saw it as a defect, which consequently created an
571 under-segmentation (Figure 9 (b)). The under-segmentation can also occur
on the trunk of conifer in the case of connected branch scars (Figure 9 (c)).

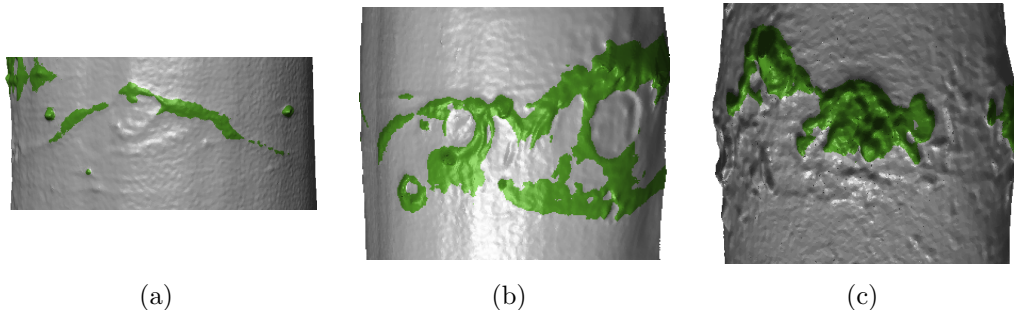


Figure 9: Examples of over-segmentation on beech (a), under-segmentation on beech (b) and on spruce (c). Within each image, all connected green areas belong to the same defect.

572

573 As the segmentation is the step preceding the classification, the perfor-

574 mance of the classification algorithm also depends on the performance of
575 the segmentation step. Thus, any improvement in segmentation will result
576 in a better classification. The most important parameters were the patch
577 size and the bin width of the histogram used to find the threshold by the
578 Rosin’s method (Rosin, 2001), and the voxel size used to compute the cen-
579 terline. Their choices were described in detail in Nguyen et al. (2016a). As
580 mentioned earlier, the over and under-segmentation can occur in the seg-
581 mentation step especially through the defect clustering through a Euclidean
582 distance filter. These errors can affect the classification, and consequently,
583 the assessment of the tree quality. In addition to the influence of misclassifi-
584 cation, the over-segmentation increased the number of defects and decreased
585 their dimension. By contrast, the under-segmentation decreased the number
586 of defects and increased their dimensions.

587 *4.2. Defect classification*

588 Visually, we can see that our algorithms were able to detect and classify
589 most of the defects (Figure 7), including small defects such as picot and bud
590 clusters. Based on Table 4, the overall classification result was good, with
591 a micro-averaged F_1 score of 0.86 and a macro-averaged score of 0.73. The
592 result was promising, particularly on the classification of branch and burl.
593 However, we did not obtain a very high F_1 score (0.46) on the small defect
594 because, first, we could not totally remove all the false positives and, second,
595 there was some confusion between the classes due to the very high intra-class
596 variability and the interclass similarity.

597 For example, the confusion between branch scars and burls can be ex-
598 plained by the fact that some burls containing only buds have a shape that

599 looks like a branch scar because both are flat. In the field, human eyes can
600 easily distinguish these two defect types; however, in the point cloud or mesh,
601 it could be difficult to distinguish them. For small-sized defects, the confu-
602 sion between burls and small defects can merely be explained by the initial
603 definition of burl and small defect. When a burl is composed only of buds it
604 might have a similar shape to a bud cluster. In our database, small defect
605 types include several biological defect types: a bud cluster with less than six
606 buds, sphaeroblast, and picot. A bud cluster may have a shape similar to a
607 small burl. The confusion was high, even for expert eyes.

608 With the objective of wood quality assessment, subclasses considering
609 the size of defects with the same biological origin can be useful to refine
610 the analysis in future studies but need a suitable assessment of the defect
611 characteristics by algorithms, which is beyond the scope of this paper. More
612 generally, it addresses the problem of a combination of defects that occurs
613 rather frequently because they have the same origin and correspond to dif-
614 ferent stages of development or because they result from a spatial proximity,
615 as in examples illustrating under-segmentation in Figure 9. Improvements
616 could be a more refined algorithm for merging close protruding areas and
617 a detailed definition of the defect types, adding size classes linked to the
618 resulting quality impact as already mentioned.

619 *4.2.1. Influence of species and bark roughness*

620 As a non-intuitive result (coming from the easier visual assessment of the
621 defects on smooth bark), a lower F_1 score was observed on beech compared
622 with oak (Table 4). In the segmentation step, on trees with furrowed bark,
623 there were many more false positives, resulting of the misdetection of bark

624 portions as defects. This is in agreement with our hypothesis. However, the
625 false positives on trees with furrowed bark had a common shape created by
626 the pattern of the rhytidome, and they were easily detectable and removed
627 by the classification through the definition of the Bark class. In contrast, on
628 trees with smooth bark, the false positives were created by bark portions,
629 very similar to actual defects in terms of protrusion and spatial distribution.
630 Moreover, on species with smooth bark, and particularly on beech, we also
631 observed many wrinkles or cambium alterations revealed by the elliptical
632 shape (*Nectria* disease) of bark (Figure 10). These alterations were often
633 misclassified by our algorithm as branch scars rather logically in the absence
634 of more relevant type definition corresponding to these singularities. Thus,
635 the classification algorithm has a higher performance on furrowed bark trees
636 than on smooth bark trees.

637 4.2.2. *Parameters of random forests and future improvements*

638 Random forests have only two principal parameters: the number of trees
639 in the forest (*nbTrees*) and the number of variables (*nbVariables*) used to
640 select and test for the best split when growing the trees. Their performance
641 was slightly influenced by the number of trees if it was chosen sufficiently
642 high (1,000 trees in our experiment). With the number of trees over 1,000,
643 the performance gain was minimal. *nbVariables* was chosen following the
644 OpenCV recommendation, which was $\sqrt{\text{variables}}$. We also noticed that
645 random forests are very robust to over-fitting so the feature selection is less
646 critical. Random forests can give a good performance, even with a small
647 training dataset (Rodriguez-Galiano et al., 2012); however, it depends also
648 on the intra-class variability of the defect class. Because burl and branch scar

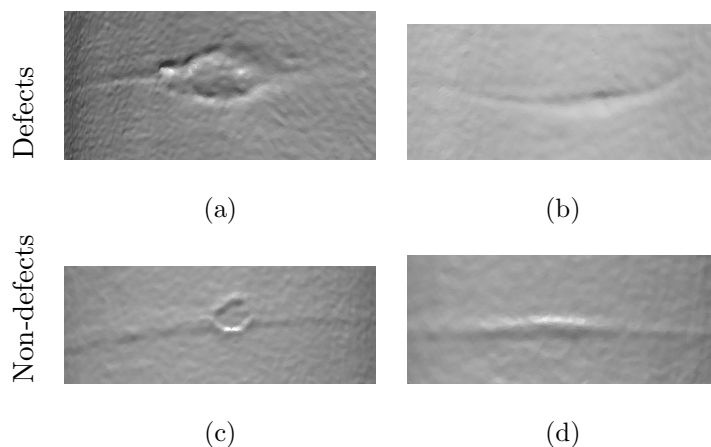


Figure 10: Examples of equivalent bark appearances considered either to be a branch scar ((a) and (b)) or a non-defect ((c) and (d)). This has been determined according to our own biological expertise. This figure illustrates the difficulty distinguish between defects and non-defects. The region in (c), while having a shape similar to a branch scar as in (a), is a scar resulting from slight damages due to *Nectria* attack affecting just the bark and not the wood below. The region in (d) has been considered as non-defect since it was formed by the covering of a dead bud during the very first years of tree development with no consequence for the wood quality.

649 have a high intra-class variability, in future work, we would like to add more
 650 training data of these types. As the incident angle of laser beams changes
 651 with the different heights of the trunk, it is also important to have the defect
 652 data from different trunk heights.

653 Another suggestion to improve the performance of the classification is to
 654 remove species in the feature vector and separately train random forests for
 655 each species, considering that the information on the species is a prerequisite
 656 brought by an operator or by another identification step (Othmani et al.,
 657 2013). This approach might have a better performance but requires more

658 training data. Our test carried out with data of the most present species
659 (beech) in our database did not clearly outperform random forests trained
660 with all species. The $F_{\mu 1}$ were 0.71 for random forests trained with only
661 beech defects and 0.70 for random forests trained with all species defects.

662 *4.3. Use for grading trunk quality*

663 The performance of defect classification can influence the grading result
664 of standing trees. Nonetheless, the impact of the misclassification of class
665 on the quality assessment is difficult to assess. The most important is the
666 classification of large defects. Once there is an occurrence of these large
667 defects, the occurrence of smaller defects is less important. However, in the
668 case of highest quality trunk, the classification performance is more critical
669 because one misclassification, even of a small defect, can result in a change
670 to a higher or lower quality class. Thus, a further development of the current
671 method is needed to measure the defect dimension which is required to assess
672 the impact of defects by a standard (AFNOR, 1999a,b, 2012).

673 Regarding the current scanning setting, the spatial resolution does not
674 allow for classifying between a picot and a less important small defect, such
675 as bud cluster. Only one picot is allowed in the case of highest quality trunk.
676 Thus, in the case that there is only the occurrence of small defects, an addi-
677 tional expert inspection could be suggested to verify the classification result
678 in the case of high commercial value. Beyond grading issues, the informa-
679 tion about defect type and position on the log can be used to optimize the
680 transformation, with the objective of increasing the volume of high-quality
681 products but such exceeds the scope of this paper even if it is a real prospect.

682 As a common problem for the remote sensing technologies, the quality of

683 TLS data can be limited by the occlusion, especially when there are branches
684 on the trunk or false positive created by moss (*Musci L.*) or lichens. In
685 general, scanning the tree from multiple views can reduce occlusions, as the
686 occlusion on the high part of the tree is difficult to avoid.

687 5. Conclusions

688 In this paper, we have presented a random forests-based classifier to iden-
689 tify defects on trunk surface from TLS data. The potential defects were
690 detected by our segmentation algorithm (Nguyen et al., 2016b). Each de-
691 tected defect was then classified into one of the four defect classes or bark
692 using the random forests classifier. Our experiment showed that from the
693 high-density data acquired by TLS, we can detect and classify most of the
694 defects on tree bark. The overall $F_{\mu 1}$ score of the classification algorithm was
695 0.86. These preliminary results are thus very promising. We could further
696 improve the score with the addition of more data and with the definition
697 of defect subclasses considering not only their biological type but also their
698 size and impact on wood quality. An interesting option will be to train the
699 random forests separately for each tree species. The information about the
700 defect type in addition to its dimension and position can be used to assess
701 the quality of roundwood or standing tree. This is the first step towards
702 developments for helping experts in the assessment of the quality of standing
703 trees or timber logs in forests or for enhancing the knowledge coming from
704 true shape scanners in the primary wood processing industry.

705 **Acknowledgments**

706 This work was supported by the French National Research Agency through
707 the Laboratory of Excellence ARBRE (ANR-12-LABXARBRE-01) and by
708 the Lorraine French Region. We would like to thank Florian Vast for provid-
709 ing technical support and for scanning and measuring the trees used in this
710 research.

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