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A new algorithm to automatically detect the pith on rough log-end images

Rémi Decelle

Université de Lorraine, LORIA, UMR 7503, 54506 Vandœuvre-lès-Nancy, France, remi.decelle@loria.fr

Phuc Ngo

Université de Lorraine, LORIA, UMR 7503, 54506 Vandœuvre-lès-Nancy, France

Isabelle Debled-Rennesson

Université de Lorraine, LORIA, UMR 7503, 54506 Vandœuvre-lès-Nancy, France

Frederic Mothe

Université de Lorraine, AgroParisTech, Inra, Silva, F-54000 Nancy, France

Fleur Longuetaud

Université de Lorraine, AgroParisTech, Inra, Silva, F-54000 Nancy, France

Abstract

X-ray computer tomography has proved to be efficient for measuring internal and external characteristics of logs that are relevant for estimating wood quality at the sawmill. However, this technology remains expensive (two sawmills in France are equipped) and there is a need to provide low-cost tools for smaller sawmills. It could help them become more competitive. There is also a need for new tools available everywhere, for example to estimate wood quality on the harvester, at the road side, or on the log yard (e.g. with mobile-phone cameras). Contrary to X-ray scans, low-cost cameras provide very different images.

Moreover few works have been done on such cameras so far. The pith in log end images is an important feature. It is usually required to detect other wood characteristics (for example annual rings) and to process further toward wood quality estimation. The pith's location is a real challenging problem for untreated log ends. In this context, we propose a robust and efficient algorithm to address this challenge. It consists of a mixture between Hough Transform and an approach based on state-of-the-art algorithms, known as Hough-based algorithms.

We validated the proposed method on RGB images of Douglas fir taken with a digital camera after harvesting wood in the forest. The obtained results show a better detection of the pith on rough log end images than some state-of-the-art algorithms. The algorithm may process images in real-time which is compatible with sawmill requirements.

Keywords: Wood, Pith Detection, Tree Rings Analysis, Hough Transform

Introduction

The quality of wood influences both its price and its use. For wood quality estimation, one of the key features to detect is the pith location. More precisely, pith location allows to analyze tree rings easier. For instance, detecting tree rings or computing average annual ring width require pith location. Annual ring width is a great indicator of wood quality. The wider tree rings are, the better quality is. Moreover, knowing how far the pith is located from the geometric center of a cross-section is an other important information of wood quality. It is an indicator of the presence of reaction wood that may affect mechanical properties. Reaction wood is a special wood that helps the tree to straighten vertically.

The problem of detecting automatically the pith has already been studied in the literature (Hanning et al. 2003, Longuetaud et al. 2004, Entacher et al. 2007, Norell and Borgefors 2008, Boukadida et al. 2012, Schraml and Uhl 2013, Kurdthongmee et al. 2018). Many methods have been developed for X-ray computed tomographic (CT) images (Hanning et al. 2003, Longuetaud et al. 2004, Entacher et al. 2007, Boukadida et

al. 2012). A CT scanner is an investment too heavy for most sawmills. In parallel, low-cost cameras such as RGB cameras provide images at lower cost with higher resolution. But dirt or sawing marks are visible on such images, which makes analysis harder. Three methods (Norell and Borgefors 2008, Schraml and Uhl 2013, Kurdthongmee et al. 2018) have proposed algorithms for pith detection on such images of untreated wood cross-sections. Wei et al. (Wei et al. 2012) provide a short survey of pith location estimation.

The three methods in the literature (Norell and Borgefors 2008, Schraml and Uhl 2013, Kurdthongmee et al. 2018) are robust and give the pith location with a millimetric precision. But they require some requirements. Norell (Norell and Borgefors 2008) manually segment their images. Both Kurdthongmee (Kurdthongmee et al. 2018) and Schraml (Schraml and Uhl 2013) assume that the wood section is centered in the image.

In our study, the wood section is neither segmented nor centered in the image. Moreover, we would like to develop a method to be used anywhere, both in forests and in sawmills environment. To the best of our knowledge, such a method has not been developed so far. In this paper, we propose a robust method for detecting the pith location. It consists of two steps. The first one aims at looking for a point on the wood section. It uses Hough Transform for circle detection. The second one is based on the state-of-the-art approach. It aims at estimating precisely the pith location.

We first describe image sets and algorithm developed to estimate the pith position. Then, we present the obtained results. After that we discuss about our method and we finally conclude.

Materials and method

Imagesets

We evaluated our method with two different image sets. These two datasets was created to have raw RGB images of Douglas fir, for which pith detection was never achieved. Indeed, Norell (Norell and Borgefors 2008) used Norway spruce and Scots pine Schraml (Schraml and Uhl 2013) used spruce logs and Kurdthongmee (Kurdthongmee et al. 2018) used rubberwood raw images.

The first imageset (called **Besle**) consists of 65 log end images of Douglas fir. Their size is 4320 by 3240 pixels. Images were captured just after harvesting in forest with a digital camera (Panasonic Model DMC-FZ45). Some images are shown in Figure 1. The second one (called **BBF**) consists of 16 log end images of Douglas fir. Their size is 4608 by 3456 pixels. Images were captured with a smartphone (Huawei Model ANE-LX1). Some examples are shown in Figure 1.

As we are interested in ambient light variations, dirt or sawing marks, we captured images as raw as possible. Each log has been taken several times (from 3 to 5 times) by slightly rotating or moving the camera between each view. In average, a pixel stands for 0.194mm. In our study, we considered that pith position is a unique pixel even if from a biological point of view it may occupy a larger area. Ground truths, i.e. the pith center position, have been manually assessed by two different operators.



Figure 1 — Example of images of both image sets. The first two rows of images show some images from **Besle** dataset and the last row shows images from **BBF** dataset.

A first pith estimation

Our algorithm proceeds in two steps. The first step estimates a pixel located on the wood section. We assume that the wood section can be approximated by circles. Thus, to retrieve such a point, our method relies on Hough Transform (HT).

More precisely, we first need to detect edges. For that, the images are converted into grayscale then down-sampled (by four their size). It reduces both computational time and noise between tree rings. After that, Canny Edge operator is used to retrieve tree rings. As tree rings can be described by circles, HT is used to detect circles. Normally a circle need three parameters, its center and its radius. This may lead to a very long computational time. To address that drawback, only circles with a radius within a certain range are searched. Let \mathbf{R} be the minimum radius, then our range is from \mathbf{R} to $\mathbf{R}+10$. For our experiments, we fix \mathbf{R} at the value of:

$$\mathbf{R} = \frac{1}{3} \min(\text{height}, \text{width})$$

where height and width are image dimension. Indeed, we noticed that in our dataset, log ends constitute around a third of an image.

Once circles have been found, we need to retrieve a first pith estimation. In order to achieve that, each circles' center assign a weight to each pixel. Those weights are equal to a 2D gaussian with a standard deviation of σ and centered at circle's center. We sum all weights for a pixel. After normalizing these weights, we could interpret weights as the conditional probability of the pith to be there given circles' center. We fix σ at the value of 50.

Figure 2 shows detected circles and the results of all weights for one image.

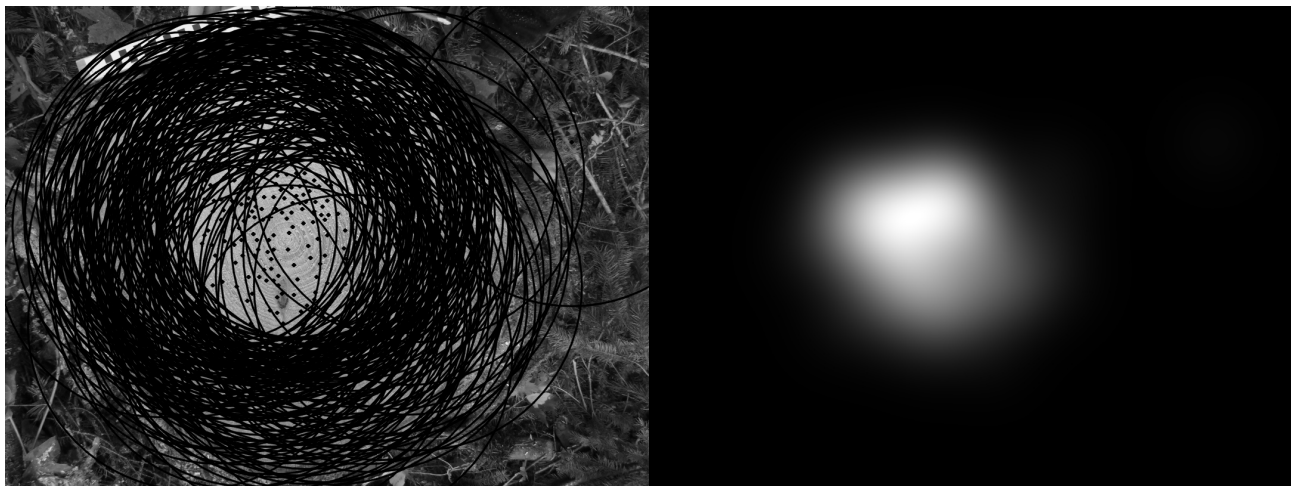


Figure 2 — On left, all detected circles by Hough Transform. On right, results after summing all weights for each circles' center.

A second more accurate pith estimation

We assume that the previous computed point is located on the wood section. If it is not the case, this second step leads to a wrong estimation of the pith location. This second step provides a more accurate pith location than the previous one. Our own algorithm is an improved version of the state-of-the-art algorithm. We assume that it could provide the expected results as we are now in an area close to the pith. Here is how we process:

1. Process the original image: convert into grayscale image, approximate laplacian filter (by the difference of two gaussian filters) and downsample the image;
2. Compute the gradient, its norm and the associated orientation;
3. Extract sub-image (preprocessed image and gradient orientation) of size ω by ω centered on the previous pith position;
4. Threshold the sub-image of the preprocessed image. We choose an triangle threshold (Zack 1977);
5. For each edge point (pixels above the previous threshold), draw a line in the gradient orientation previously computed. An accumulation is then obtained;

6. Filter the accumulation image with a median filter. It has to reduce local peaks due to wrongly computed gradient orientation (Norell and Borgefors 2008);
7. Threshold the filtered accumulation image with a level of τ times its maximum (only values above are kept). A similar step has been proposed by Norell (Norell and Borgefors 2008);
8. Estimate new pith position, the barycenter of remaining pixels after the previous threshold;
9. Compute the euclidean distance between the new position and the old one. If it is below a thresh, stop the algorithm, otherwise iterate steps 3-9 again with the new pith position. Stop the process no matter what happens after some iterations.

Results and discussion

We optimized our algorithm on **Besle** dataset then we validated it on **BBF** dataset. To set the parameters we defined arbitrarily a set of values for each parameter and tried each possible combination. We minimized, over the whole **Besle** dataset, the sum of distances between ground truths and results. We have compared our results with those obtained by our implementation of the algorithm of Kurdthongmee (Kurdthongmee et al. 2018) on our datasets. We optimized the required parameters.

Figure 3 shows results for both datasets and both algorithms. Our proposed method is more accurate. On **Besle** dataset, our method outputs a mean of 14.29mm while Kurdthongmee's algorithm outputs a mean of 25.05mm. Our results are confirmed by **BBF** dataset (see respectively Figure 3 and Figure 4) with a mean of 22.77mm against 27.81mm. We consider that a pith estimation is not accurate if the distance between ground truths and the estimation is over 5mm. Therefore, our method is able to provide a precise pith estimation for 53 images, i.e. 65% of both datasets. Kurdthongmee's method provides such results for 8 images, i.e. 10% of both datasets.

Our algorithm is a little slower than Kurgthongmee's one but still able to process in real-time. In average, one image is processed in 4956ms for our algorithm and 667ms for Kurdthongmee's one. Our experiments were performed on an Intel Core i7 with 2,5 GHz and 16GB RAM.

Figure 4 shows some examples in which our method failed to find the pith. This lack of precision is due to the second step. Indeed, the first pith estimation (pink cross) is on the cross-section, but the second estimation (yellow star) do not stay on the real pith. This error may be imputable to parameters which are not enough optimized.

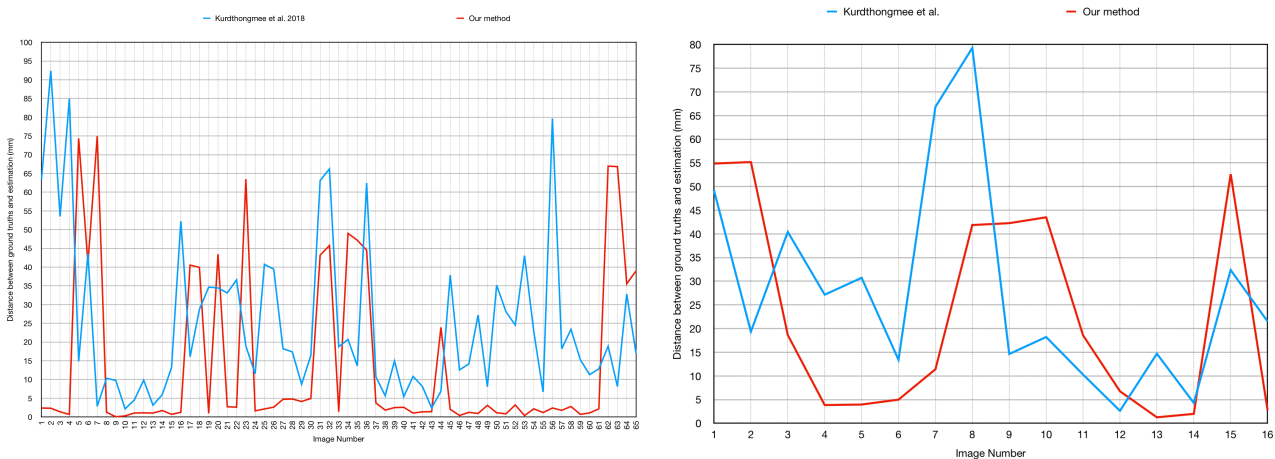


Figure 3 — Comparison of the distance (mm) between ground truths and estimated pith location for **Besle** dataset on left and **BBF** on right. In red line, our results after the full process. In blue dotted line, our results after the first step (only with agents). In green line, obtained results with method proposed by Kurdthongmee (Kurdthongmee et al. 2018)



Figure 4 — Some cases where our method fails to detect precisely (less than 5mm) the pith. In red cross results of the first step, and in yellow star the results after the second step. The first two cases show the same log end but with a slight rotation. The error can be explained by a high presence of sawing marks, knot near the pith and green dirt near the pith. The third failure can also be explained by a high presence of sawing marks.

Conclusions

In this paper, we proposed a method able to estimate pith location on images captured by digital cameras or smartphone's camera. The raw images were processed directly with no prior segmentation nor cropping. We do not assume that the geometric center of the image is located on wood cross-section. To the best of our knowledge, no method has been developed in such a case. Despite this, we compared our method with another one. Experiments were performed on two datasets of log end images of Douglas fir. The results showed a better accurate estimation on both datasets.

However, this accuracy leads to more computational time and some pith estimation are not as precise as we have aimed. At the moment only one wood specie has been processed.

Future works should focus on improving the first step of detection which may lead to a better pith estimation.

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