Board localization within logs using image analysis approaches for traceability and quality assessment in sawmills

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Context and objectives

Structural design of buildings requires the knowledge of the material that used in construction. On the opposite of concrete and steel, timber mechanical properties are highly variable because of tree growth conditions and the natural heterogeneity of wood. This is the reason why quality assessment is crucial for timber. In modern sawmills, there are scanners that control each board quality thanks to color or X-ray images. The LaBoMaP has a great experience on how to extract boards mechanical properties from scanner data. Recently, the scanner data has also been used for the traceability of boards. Board traceability data can help for quality assessment because there are correlations between boards' quality and the log they belong to, or at a larger scale the region they come from. And some works on log end image processing have been already performed in the literature (Decelle et al. 2021).

This study is part of the ANR project EffiQuAss, which aims to develop algorithms that are able to recognize wooden boards and to obtain their locations from log images taken in the sawmill. This information can be used to improve timber quality assessment.

Material and methods

The available dataset includes images and measurements at different steps of the sawing process of Douglas fir logs from the sawmill. A total of 16 logs of different diameters, about 2.8 m long, were considered. As illustrated in Fig. 1, the log-ends were photographed on the log-yard with a Canon EOS 2000D camera. The distance between the camera and the log-end (or board pile) was kept at 1.04 meters to maintain the same scale. The logs were then sawn with different sawing patterns to produce boards of same size of section either 48 mm x 135 mm or 48 mm x 156 mm with one or two stacks of boards depending on the log diameter. An example is given in Fig. 2 (a), which is a sawing pattern with two stacks of six boards each for log #2. After sawing, the boards were photographed as shown in Fig. 2 (b), with the board number handwritten on a whiteboard so that they can be rearranged. The complete dataset of 16 logs and 162 segmented board images is available at https://zenodo.org/record/7123764#.YzsOeqTP2Uk.

The purpose of this study is to “reconstruct the log” from the segmented images of the boards belonging to the considered log. That is, to place each board in the log in the position it was before sawing. The methods for image matching are used to solve this problem. Image matching methods can be classified in two categories: templated-based and feature-based techniques (Dong 2013, Swaroop and Sharma 2016, Lowe 2003, Gollapudi 2019). The template-based methods operate directly on the pixel values; e.g., normalized cross correlation (NCC)

(Swaroop and Sharma 2016). These methods are simple and intuitive, but tend to fail when images have large rotations, large illumination levels, large scale differences, etc. Conversely, the feature-based methods are generally invariant to scale, rotation, and illumination, etc. Among them, the scale invariant feature transform (SIFT) (Lowe 2003) method is most common. However, as with other feature-based algorithms, its matching performance depends strongly on the quality of feature extraction, which is sensible to noise.

(a) (b)

Fig. 1: Images of log #02: log end image taken on the log-yard ; the corresponding manually segmented log image.

(a) (b)

Fig. 2: (a) Manual positioning of the board end image for log #02 (flip means that the board end image had to be flipped to be in the right orientation); (b) A pile of boards from log #02.

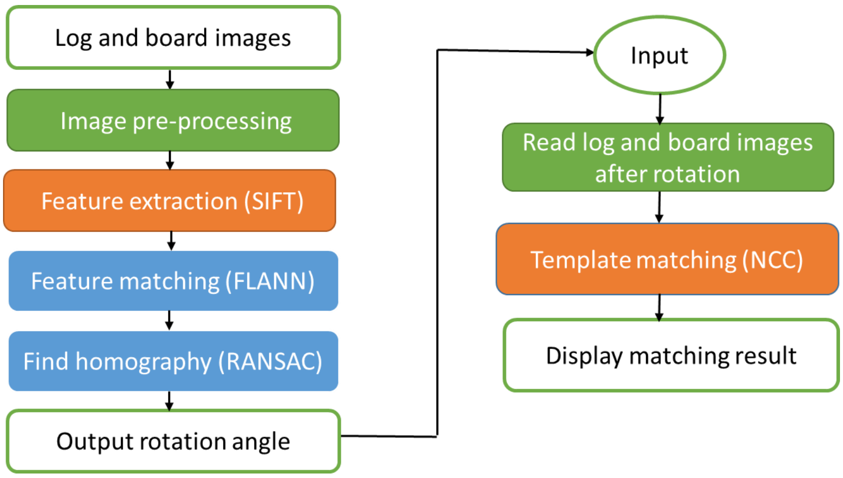

Fig.3: Flowchart of the board recognition algorithm.

To achieve our goal, SIFT and NCC are combined to improve their performance in image recognition. More specially, in the pre-processing procedure, the RGB images are converted to grayscale and then enhanced by histogram equalization method. After feature detection and extraction by SIFT, Fast Library for Approximate Nearest Neighbors (FLANN) (Muja and Lowe 2009) is applied for feature matching. Then, RANdom SAmple Consensus (RANSAC) (Yan 2022) algorithm is used to localize board images. However, not all the boards are found in each log image at this step. This may be caused by disturbances present in digital images, such as sawing marks, dirt or changes in ambient light. Nevertheless, using these determined board positions, we can easily calculate the rotation angle of the log image relative to its board images. After rotating the log image, the NCC is finally performed to determine each board position on the logs. The flowchart of our proposed algorithm is given in Fig. 3.

First results

In this section, we evaluate the feasibility and effectiveness of the proposed method on the available dataset. As displayed in Fig. 4, only three boards are recognized successfully by SIFT. From this, the rotation angle of the log can be estimated. In addition, the rotation angles obtained from SIFT for 16 logs are presented in Tab. 1.

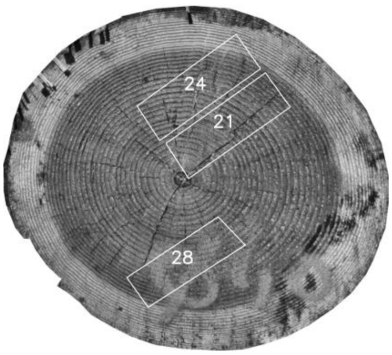

Fig. 4: Recognition results of log #2 by SIFT

Tab. 1: Rotation angles obtained by SIFT for 16 logs

Log#	01	02	03	04	05	06	07	08
Rotation angle	34.7°	35.5°	78.9°	314.6°	27.9°	72.1°	39.5°	44.3°
Log#	09	10	11	12	13	14	15	16
Rotation angle	320.7°	77.2°	288.5°	2.8°	219.1°	321.4°	101.4°	341.7°

Then, after rotating the log images to the horizontal direction according to the boards, the template matching with NCC is performed. A recognition result is shown in Fig. 5. Fig. 5 (a) is the board recognition results by the proposed method, while Fig. 5 (b) is the manual positioning results of the board end image on the end image of log #2, it can be observed that the positions of all 12 boards on log #2 were successfully identified. Moreover, the success rate of correctly placed boards for 16 logs was calculated to be over 98%. However, for the sake of brevity, the board recognition results for other 15 logs are not presented here. All the obtained results are available for download at https://zenodo.org/record/7123764#.YzsOeqTP2Uk.

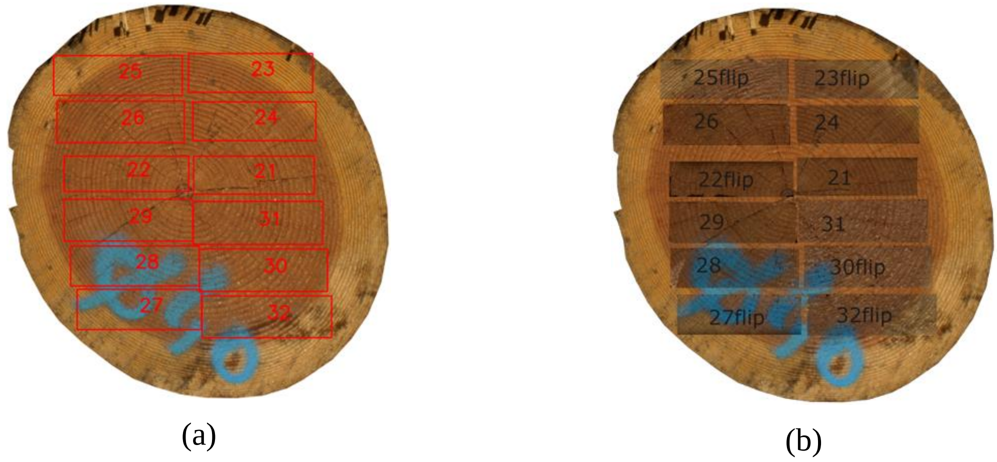

Fig. 5: (a) Final board recognition results on log #02; (b) Manual positioning of the board end image on the end image of log #02.

Conclusion and perspectives

The feasibility and effectiveness of the proposed method (the combination of SIFT and NCC) are visually verified from our board recognition results. In future works, instead of using visuals to evaluate the results, more convincing and accurate evaluation metrics such as Intersection over Union (IoU) and mean average precision (mAP) will be used to evaluate quantitatively the precision of our method. Further development is still needed to test the method on more different sawing patterns. Furthermore, the next step in the traceability process would consist in recognizing from which log different boards belonging to.

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