Supplementary Materials for "Ellipse Detection and Localization with Applications to Knots in Sawn Lumber Images"

Shenyi Pan*
University of British Columbia
shenyi.pan@stat.ubc.ca

Shuxian Fan*
University of Washington
fansx@uw.edu

Samuel W.K. Wong
University of Waterloo
samuel.wong@uwaterloo.ca

James V. Zidek
University of British Columbia
jim@stat.ubc.ca

Helge Rhodin
University of British Columbia
rhodin@cs.ubc.ca

1. Equipment and Methods

To demonstrate the methodology proposed in this paper, we scanned the lumber specimens in the wood products testing laboratory at FPInnovations. The lumber species used in this experimental study is Douglas Fir (DF) lumber, which is widely used to make dimensional lumber. The DF specimens are of dimension $2'' \times 6'' \times 12'$. The selected specimens represent a test material with adequate variation in appearance to ensure a good sample for studying different knot patterns, which could arise from different tree growth conditions and sawing practices. The total number of specimens used in this study was 113.

As shown in Figure 1, the lumber scanner is equipped with two sets of digital cameras. The set of cameras that take the color images of the lumber surfaces are Camera 2 and Camera 3, which, however, cannot be seen from Figure 1. For illustrative purposes, a schematic setup of the color cameras is given in Figure 2.

The issue of pixel misalignment results from the setting used in the lumber scanner, where each lumber specimen is sent to the camera through rollers at a fixed speed. The two color cameras frequently take images at the same time from both the top and side of the specimen. The scanner produces lumber images using its built-in image stitching methods. For each lumber specimen, four color images in PNG format are generated with a resolution of 8000×2048 pixels. Note that although each piece of lumber has six sides, the two ends are typically ignored since their area is much smaller than the other four sides. As natural materials, sawn lumber does not necessarily have perfectly flat surfaces. As a result, inevitable 'bumpiness' is generated when a piece of lumber is scanned as the image stitching algorithm cannot automatically recognize random shifts of the lumber surface. This leads to the misalignment of pixels in the scanned output images, and a similar phenomenon can also occur when applying computer vision-based industrial inspection on other materials that are scanned on rollers.

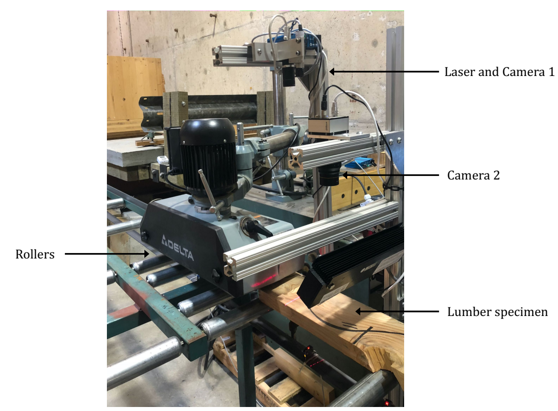


Figure 1: Setup of the lumber scanner. The lumber specimen can be seen at the lower right corner of the figure, on the rollers on which it moves it forward at a constant speed under the cameras.

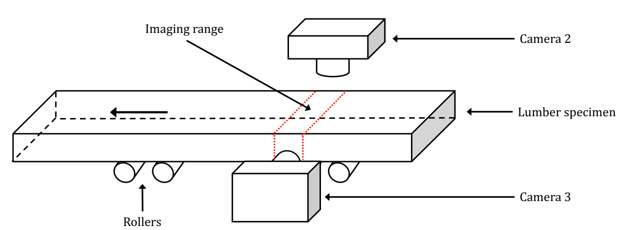


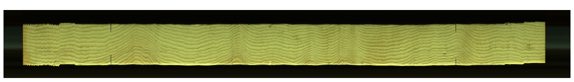
Figure 2: Schematic diagram of the color camera setup.

*Authors contributed equally.

2. Image Preprocessing: Comparisons with Method Based on Threshold

Raw scanned images of lumber specimens exhibit different levels of distortions. Lumber specimens experience the most ‘bumping’ at the beginning and end of the scanning process, often causing the most severe distortions to occur at the two ends of the scanned images for a piece of lumber.

Figure 3 shows four most common cases of image distortions in the dataset. Figures 3a and 3b correspond to the cases when there are moderate distortions. Lumber images in these two figures show minor pixel misalignment at the two ends. The middle part of the lumber images bends slightly, which may be caused by mild bumping or irregular shapes of the sawn lumber. Figures 3c and 3d are the cases of severe distortions, where pixel misalignment is distinct and consistent across the entire piece of lumber. Common defects such as knots or cracks appear in similar colors to the background in the scanned images. They are most frequently found on edges of the lumber specimen. Figure 3 also shows that the background color of the raw images is not uniformly black.



(a) Moderate distortion with no or minor defects

(b) Moderate distortion with evident defects

(c) Severe distortion with no or minor defects

(d) Severe distortion with evident defects

Figure 3: Examples of common distortion cases in the dataset.

These features of raw images make it a challenging task to align the pixels simply by shifting the columns of pixels based on a given threshold. In the preliminary analysis, we experimented with the method based on threshold to fix the pixel misalignment in the raw images. We first transform the color images to grey scale. For each column of pixels, we then find the position of the first pixel has values greater than the threshold and shift the entire column to offset the difference.

This method works reasonably well for specimens with almost clear surfaces as shown in Figure 4a. However, it is not robust to the presence of common lumber defects such knots or cracks. In Figure 4b, the pixel misalignment is not correctly fixed, especially around knot areas where the color of the knot is similar to the background color. In Figure 4c, the alignment fails around the cracks. Moreover, due to the non-uniform background color, the threshold method may fail and generate images with non-smooth edges as shown in Figure 4d.

In contrast, our proposed method is more robust to the presence of common defects as well as non-uniform background color. Figure 5 shows the images processed using our proposed method in the four cases.

(a) Moderate distortion with no or minor defects

(b) Moderate distortion with evident defects

(c) Severe distortion with no or minor defects

(d) Severe distortion with evident defects

Figure 4: Results of images processed using the method based on threshold.

(a) Moderate distortion with no or minor defects

(b) Moderate distortion with evident defects

(c) Severe distortion with no or minor defects

(d) Severe distortion with evident defects

Figure 5: Results of images processed using our proposed method.