RECOGNITION OF SAWN TIMBER USING TEMPLATE MATCHING

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ABSTRACT

As the wood industry increases its level of automation, there is a growing need for more advanced machines that use cameras to aid in the decision-making. In the EU project Hol-I-Wood Patching Robot an entirely autonomous inspection- and patching system has been designed, which needs to be able to identify individual wood panels for customized treatment.

Template Matching is an image processing method commonly used to find and inspect objects in images. It is a robust method which in its normalized version can find objects even under different lighting conditions. The purpose of this paper is to investigate the accuracy and computational speed of template matching for recognition of sawn timber. The idea is to resize (shrink) the images of the sawn timber to a low resolution in order to increase the computational speed.

A previously scanned dataset of 886 Scots pine (*Pinus sylvestris* L.) boards were used as a database. To evaluate the proposed board recognition method, 44 of the boards in this database were rescanned and matched to the larger dataset. The sawn timber images were resized to resolutions in the interval 0.04 to 0.16 pixels/mm and the accuracy and computational speed were measured for each case. The matching software was implemented in the open source software package OpenCV due to its optimized code.

The conducted tests resulted in recognition rates above 99% for image resolutions higher than or equal to 0.06 pixels/mm. Template matching is probably a good choice for recognition of sawn timber in industrial applications.

Keywords: Image processing, Sawmill, Sawn timber, Traceability, Wood.

INTRODUCTION

Tracking of individual pieces of sawn timber between processing steps in sawmills enables detailed process control. Diagnostics and process surveillance that enable continuous improvement of the industrial processes could be based on statistics of each individual piece of sawn timber instead of on statistics at a batch level. The drying process is one example that could be analyzed in detail by measuring individual pieces of sawn timber before and after. Without an automatic recognition system for sawn timber, such studies can only be done using labor-intensive and process-disruptive manual tests.

Invasive recognition and tracking in the wood value chain have been studied previously using barcode labels, paint and radio frequency identification (RFID) (1-3). Non-invasive methods for recognizing boards have previously been evaluated using scale and rotationally invariant feature descriptors (4). For wooden panels, the intrinsic geometry of knot patterns has been used for recognition (5).

In digital image processing, *template matching* is a common method for detecting and recognizing objects. The method tries to locate a sub-image, a template, in a larger search image by comparing the pixel intensities. Either a similarity or a dissimilarity measure is calculated for every position in the search image. Template matching is often used in areas such as biometrics, industrial inspection, robot navigation, multimedia retrieval, and motion tracking. The normalized variants of template matching are robust in the sense that they, besides being able to detect objects in noisy environments, also can handle uniform illumination changes. Template matching does not depend on the object having any particularly distinct features to be able to detect it. However, a distinct unique look of the sought object often improves the identification accuracy.

The objective of this paper is to investigate if template matching can be used to recognize individual pieces of sawn timber under realistic conditions and in a reasonably short time. To minimize the computational cost and the memory requirement for a board fingerprint database, we have investigated the effects of resizing the images of the sawn timber to resolutions between 0.04 and 0.16 pixels/mm.

MATERIALS AND METHODS

Material

The dataset in this study consists of 886 floorboard images from Scots pine (*Pinus sylvestris* L.) with the dimension 21 × 137 mm originally scanned for a customer preference study (6-8). These boards were between 3 and 5 m in length and were sawn from 222 logs with top diameter between 201 and 215 mm that were randomly collected from Bollsta sawmill in central Sweden. The boards were planed, sanded and finished with white pigmented oil and a thin layer of varnish. These boards were scanned in 2006 using a high-resolution color line camera at a resolution of 2.5 pixels/mm lengthwise and 10 pixels/mm across. The images were later resized to 1 pixel/mm in both dimensions and are denoted as the database images.

A rescan of 44 boards included in the first dataset was carried out in 2012 and the storage period caused some of the boards to be slightly crooked or bowed. The same line camera as before was used in 2012, but with a resolution of 5.6 pixels/mm lengthwise and 6.5 pixels/mm across. The images were resized to 1 pixel/mm in both dimensions. In Figure 1, examples of these images are shown next to the original scans from 2006. Besides the differences in appearance, the images of the rescanned boards differ in several other ways to the original images: They are not rectangular due to crook, they are slightly skewed and the black areas beside the boards have not been cropped out, as shown in Figure 2. Overall the images have similar characteristics as if they would have been acquired in the industry. To get a larger dataset, two images were extracted from each end of the 44 rescanned boards as described in Figure 3.

Board fingerprints

To recognize a board, a description needs to be stored in a database for later lookup. The description is called the *fingerprint* and needs to be unique with respect to other fingerprints. In this study, the fingerprint is in practice a two-dimensional grayscale copy of the image of the board, but rescaled in both dimensions to a resolution between 0.04 and 0.16 pixels/mm. Three examples are shown in Figure 4 with resolutions of 0.04 pixels/mm, 0.08 pixels/mm, and 0.12 pixels/mm. The pixel intensity values are stored in 8 bit depth. As an example, a 137 × 4000 mm board rescaled to 0.1 pixels/mm requires $(137 \times 0.1) \times (4000 \times 0.1) \times 8$ bits ≈ 43840 bits = 5.48 kilobytes of memory.

Figure 1: Example of a few boards from the floorboard dataset scanned at two different occasions (board lengths have been cropped to fit the page). Dark pixel regions have been cropped away from the rescanned boards (the lower of each image pair) to better show the differences in brightness.

For the matching to work optimally, all fingerprints need to be rectangular. The database images are already rectangular, but the crooked boards in the query images have to be straightened. It is also important for the computational speed of template matching that the dark image regions outside of the boards in the query images are removed. In this study, these two factors were dealt with by pre-processing the query images before shrinking them using the following steps:

1. For each column in the image, extract the pixels belonging to the board using a specified threshold value. This step results in n pixel arrays, where n is the number of columns in the image.
2. Calculate the median width, w, of the extracted pixel arrays and remove all pixel arrays (columns) at the start and end of the image that fall below $0.9w$. Empty columns are thus removed.
3. Resize the pixel arrays using linear interpolation so that they also get the median length w.

These steps remove both crook and also eventual skew of the boards in the query images and result in rectangular images. The resulting images are then shrunk to create the query fingerprints. The database fingerprints are created by shrinking the database images without pre-processing.

Matching fingerprints

In this study, the proposed method of matching a query fingerprint to a fingerprint in a database is using template matching. The query fingerprint is the template and the database fingerprint is the search space. To negate pixel intensity offsets in the images, the mean pixel values are subtracted from both images before performing the template matching.

Figure 5 shows the concepts of template matching as it was performed in this study. When the boards have the same width, as was the case in this study, the template matching becomes unidimensional, which reduces the number of calculations and thus the computation time. Each position of the image template generates a scalar similarity measure between the template and the specific region of the other image. For each query and database fingerprint pair, a vector of such values is created, and the maximum value is extracted and denoted the quality of the match

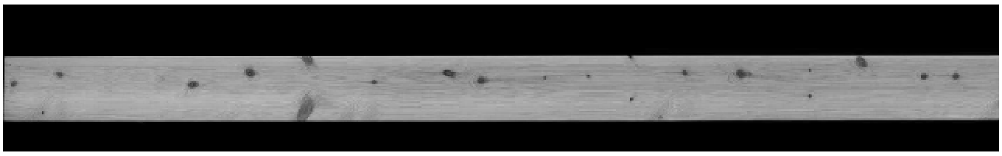

Figure 2: A rescanned board with the typical dark surroundings present in all query images. The board length has been cropped to fit the page.

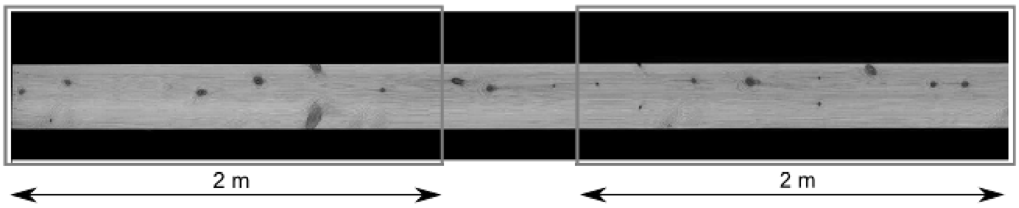

Figure 3: The rescanned boards were split into additional images. The pixels inside the rectangles were extracted to become a new dataset. The total board length has been cropped to fit the page.

between the two fingerprints. When finding the best matching fingerprint in the database for a specific query fingerprint, the quality of the match between each database fingerprint and the query is calculated. The fingerprint with the best matching quality is considered the most similar fingerprint in the database to the specific query.

When handling boards in industrial processes the orientation of boards and distances to cameras are known in general. Therefore, the fingerprints and the fingerprint matching are allowed to be scale and rotationally dependent. In this study, we choose to include the possibility that boards could be rotated 180°. The fingerprint matching handles this by, for each pair of query and database image, conducting the template matching twice. Once without changing the orientation of any image and once when the query image is rotated 180°. The quality of the match corresponds to the best position of the template both orientations considered. In practice, this means that the number of fingerprints in the database is doubled (886 × 2) compared to the hypothetical case when no change in orientation is allowed. The reason for including this check of orientation in the study was that such functionality probably would be valuable in industrial practice.

Accuracy and timing

Matching accuracy and computational time were extracted for all 7 choices of image resolution. The matching accuracy was measured as the percentage of the 88 query fingerprints that were matched to the correct fingerprint of the 886 in the database. The computational time was measured for the matching step.

As mentioned previously, the proposed board recognition method checks if the query fingerprints are flipped 180° compared to the database fingerprints. Due to this check, the matching of each query fingerprint to the database takes double the computation time and the database have in practice twice the number of query images.

The tests were performed using software written in C++, and OpenCV 2.4.7 was used for all image processing, e.g. shrinking the images and template matching. The hardware was a laptop of model HP EliteBook 8560w with Intel Core i7-2670QM processor at 2.20 GHz, 64-bit Windows 7 operating system and 8 GB RAM. The code ran exclusively on a single processor core.

Figure 4: Examples of fingerprints of a board downsampled to resolutions 0.04 pixels/mm, 0.08 pixels/mm, and 0.12 pixels/mm (top to bottom). The length has been cropped to fit the page.

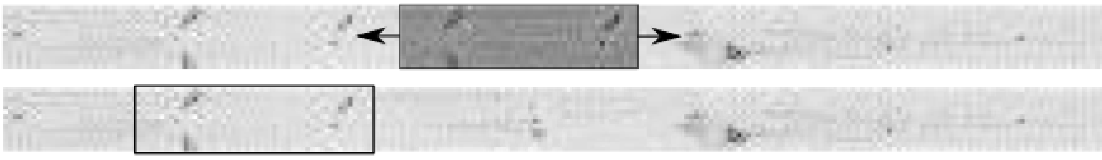

Figure 5: The upper image shows a fingerprint of a board in the database and a dark image region corresponding to a query image (in this case it is much shorter than 2 m). The mean pixel values have not been subtracted to make it easier to distinguish between the fingerprints. The query image is moved as the arrows indicate and for each possible position, the images are compared using a specific template matching algorithm. This particular pair matches each other in the position of the rectangle in the lower image.

RESULTS

The matching accuracy and computational times for the testing procedure are presented in Table 1. The image resolution needed to be 0.06 pixels/mm or higher to get a matching accuracy of at least 99%. The table presents the mean time of matching one query fingerprint to a fingerprint in the database. Thus, the time required for finding the best match for a specific query fingerprint needs to be multiplied with the number of fingerprints in the database. The computational time was strongly influenced of the image resolution.

DISCUSSION

Industrial applications

One industrial application is process control. By recognition of individual boards before and after one or several processing steps, the status of the process can be measured. Such process control can be made on a batch level without requirements of tracking of individual boards. But a higher level of detail can be achieved with recognition. For process control, the required matching accuracy is rather low as long as erroneous matches can be avoided. If only 90% of the boards can be correctly recognized and the rest are identified as erroneous, a high level of detail should still be obtained. The proposed recognition method in this paper achieves the matching accuracy requirement with ease, but the recognition method does not investigate if the best matches are likely to be erroneous. To avoid erroneous matches, the quality of the match for the two best

Table 1: Matching accuracy and computation time of the proposed board recognition method for different fingerprint resolutions. The time is for the fingerprint matching step and represents the matching of one query fingerprint to one database fingerprint.

Resolution (pix/mm)	0.04	0.06	0.08	0.1	0.12	0.14	0.16
Accuracy (%)	63	100	100	99	100	100	100
Comp. time (ms)	0.3	0.6	1.0	1.7	2.0	2.8	3.5

matches could be compared. If they are similar, the best match would have a high probability to be erroneous.

Other applications can include decision making on individual board level like cross-cutting, trimming, planing, and patching. An example is the Holi-Wood PR project where an expensive measurement system scans wooden panels and calculates where they need to be patched. In a later stage, the panels are recognized at patching robot stations that acquire the calculated patching positions from a database. These kinds of applications need a nearly perfect (100%) matching accuracy. This level of matching accuracy is acquired by the proposed recognition method making it suitable for these kinds of applications.

Time requirements for practical applications depend on the specific application, but it is reasonable to expect that it should take less than 1 s to recognize a board. For a fingerprint resolution of 0.06 pixels/mm, our recognition method can search a database consisting of $1000/0.6 \approx 1667$ boards in 1 s. The computer used in the tests was a three years old laptop so there are potential for increasing the speed of the recognition method by using a modern computer. Note however, that the larger the number of boards in the database the harder the matching problem becomes and the more time is required. In this study, the database held 886 boards, but by reducing this number the performance of the recognition method would be even better.

Improvements and limitations

The query boards in our study were 2 m, and it is expected that the matching accuracy would be even higher if boards of full length would have been used. There are two reasons for this: 1) There is more information in a larger board and it is thus higher probability that the fingerprint will be unique. 2) When it is known that the whole board is used as a query it is possible to presort the fingerprints in the database by removing all with a deviating length. Then it is vital that no cross-cutting has been performed on the boards. If all boards in the database would have the same length as the query image, then in the template matching procedure, the template would have the same size as the search space, which would greatly increase the matching speed.

Another way of making the matching accuracy higher and more robust is by using query images that are more similar to the database images than was the case in this study. Greater similarity can be achieved by using the same camera setup and lightning conditions at the locations where the database and query images are acquired. Our study used database images that were intentionally dissimilar to the query images. Since the matching accuracy was high, these combined facts indicate that the proposed recognition method is robust in this regard.

A drawback of the proposed recognition method is that it is not invariant with respect to scale and rotation. It is therefore important that the orientation and scale of the boards in the images are well defined. This is often the case in controlled environments like process industries, but is not true in general.

Material and species

This study is made on boards of Scots pine, but since wood is a material with high diversity in appearance, it is not certain that the same matching accuracy would be achieved if another material had been used. However, we expect that as long as the material has about the same contrast between light and dark areas, the recognition method would work satisfactory. The knots are in particular interesting, since the number of knots, their position, color, and size contribute to the uniqueness of the board. It would be interesting to test the algorithm on a material with very few knots or no knots at all.

There are no apparent reasons why this would not be true for boards from another species as well. We are looking forward to see future studies on how the proposed recognition method would work on different species of wood.

CONCLUSIONS

Template matching in combination with resizing board images to low resolution is a highly accurate, simple and robust method for identifying wooden boards. The speed of the proposed recognition method allows for industrial practice and it can be used to recognize boards that have been cross-cut.

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