A Machine Vision based Lumber Tracing System

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Abstract: In this paper, we introduce a machine vision system for wooden board tracing in sawmills. The goal is to match images taken from boards in the beginning and at the end of the manufacturing process in order to track the movement of individual boards. The task is challenging due to the changing appearance of boards during the process. These are changes in color, texture and physical form. Lighting conditions and camera parameters are also unknown and can change between different camera systems inside a sawmill. Before matching, image alignment is carried out using 2-D to 1-D projection signals. Signals are generated using the statistical properties of gray scale images. Aligned images are then matched using fast and compact local descriptors. The performance of the system was evaluated using over 1000 real life images captured with visual quality control cameras integrated into the production line. A tracing accuracy over 95% was achieved with a high confidence of the individual match.

1 INTRODUCTION

With advances in measurement technologies, we are approaching a point where it is possible to trace wood all the way from the harvesting location to a final product. Tracing reveals important information about how the whole wood refinement process and the efficiency of the supply chain can be improved. For example, by backtracking the logs and boards sawmills will learn which harvesting areas produce the highest quality raw material.

One part of the tracking chain is inside the sawmill. In the beginning of the process boards pass under a line or matrix camera system for quality and dimensional measurement. At the end, before packing, boards pass under a second camera system for the final visual quality classification. A system that can detect when a board has passed through the process is needed so that the board can be traced back to the log it was sawn from.

The traditional way of object identification in mass production is the use markers such as bar codes, that are added to the product. For example, commercial products for lumber tracing using painted identifiers are available. RFID tags (Sirkka, 2008) are also becoming an attractive option due to advances in wireless technologies. In addition, previous research also includes the use of microwave signatures (Fuentealba et al., 2004).

In this paper, however, we present the first approach using only features extracted from images. Compared with the other systems, which require additional equipment to be installed, camera based solutions need only additional software, since the same cameras that carry out the visual inspection can be used. This makes it possible to increase the total yield of a sawmill with only minimal investments.

Typically, the image based quality classification of boards is based on knot sizes and locations, color, shakes and other visible defects (Gu et al., 2010). However, these properties alone are not suitable for robust matching because of the changes taking place during the process. Although grain patterns in the board can experience some slight changes, we found out that these patterns are a good basis for tracing. Figure 1 shows an example of these patterns.

Finding a matching pair of two images for the same board is a challenging problem due to notable changes that the manufacturing process imposes on the appearance of the board. There are two types of changes: actual changes in the board itself caused by the process and camera induced changes such as lens distortion and focus blur. It is also highly unlikely that the lighting conditions are similar for all cameras. Different sawmills have different camera systems and in some cases all the cameras installed at one site can be of different types. Figure 2 shows some of the main anomalies including changes in color and surface tex-

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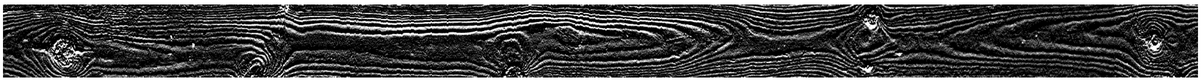

Figure 1: An example of a grain pattern image. Strongest grain are clearly visible.

Figure 2: Typical changes in the appearance of the board caused by the process. Board in the beginning up / board in the end down.

Figure 3: An example of physical change experienced by a board.

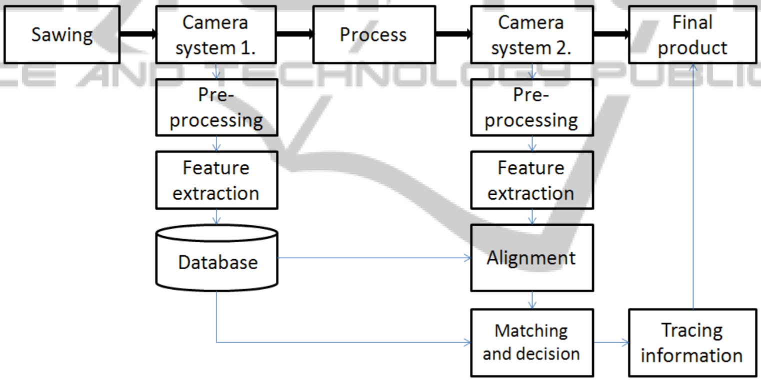

Figure 4: Layout of the production line and tracing components.

ture. Figure 3 presents a case where the physical form of the board is altered.

In our contribution, we present a complete system framework for tracing wooden boards inside a sawmill. A suitable method for fast image alignment was implemented using 2-D to 1-D projection signals. The required preprocessing steps for images are described. For matching, we evaluated two different descriptors that are claimed by their original authors to be fast and compact. Tracing performance of the system was finally tested using real life images obtained from the production line of a sawmill.

2 BOARD TRACING METHOD

The proposed method is divided into three main phases. Images are first preprocessed, resulting in a cropped gray scale image of a section of a board. For images taken in the beginning of the process, features are extracted from the board and stored to a database together with a 1-D signal which is used for alignment later. For images taken at the end of the process, 1-D signal is first formed and the translation between images is calculated. After the image alignment, features are extracted from the corresponding area. Matches between camera system 1. and camera system 2. (see Figure 4) are searched for by calculating the Euclidean distance between the final feature matrix and feature matrices stored in the database. Figure 4 illustrates the layout of the production line and the tracing system.

To be able to run board tracing at full production speed numerous things have to be taken into consideration. Firstly, the amount of raw image data is massive, in this case over 16 MB per board. Secondly, the time that is allowed for feature comparison is only a few hundred milliseconds for high production speeds. The database can contain thousands of boards meaning that the computational complexity of the match-

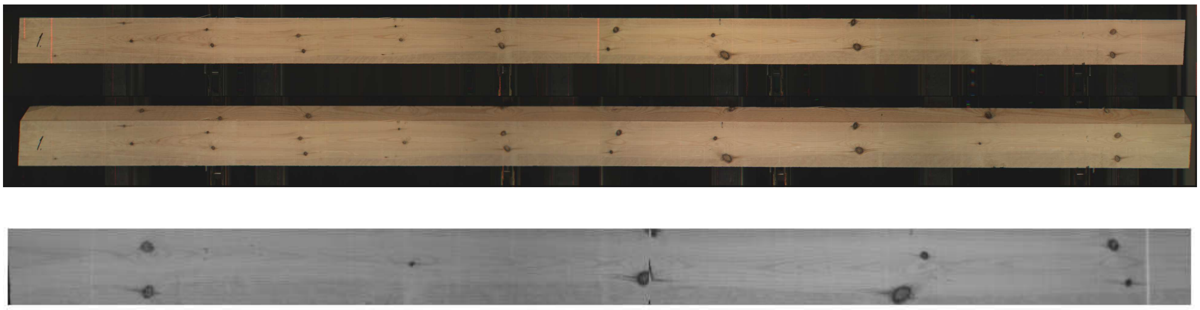

Figure 5: Original and result images of preprocessing.

Figure 6: A cropped section of a board with 1-D projection signal plotted over.

ing has to be low. Also, the need to store thousands of boards sets limits on the amount of data that can be used in the matching stage.

2.1 Image Preprocessing

The preprocessing stage is comprised of gray color transformation, cropping, segmentation, straightening and background removal. The original raw data for one board was a 6400 x 600 pixel RGB color image containing the flat and side/flat view of the board. The bottom 300 pixels containing the flat/side view is immediately cropped. The remaining area is converted to a gray scale image.

From the gray scale image the corners of the right hand side of the board are searched for using thresholding in a small sliding window. After the end of the board is found, a smaller section of N x 300 pixels is cropped, where N is the final width of the required image area. From this cropped section, the left hand side corners are searched for and the board is straightened by removing background pixels above the board and moving each row upwards equal to the removed pixels.

Although straightening induces some geometrical distortions because of the straightforward nature of the algorithm, no incorrect matches were observed due to straightening errors. Straightening also removes the need for y-directional alignment since the whole height of the board is utilized later in the feature extraction.

2.2 Feature Extraction

For an application which has strict data storage and computational time requirements the features used need to be compact and fast to compute. The two descriptors chosen here, Center-Cymmetric Local Binary Pattern (CS-LBP) (Heikkilä et al., 2009) and Upright Speeded-Up Robust Feature (U-SURF) (Bay et al., 2008), are both modified, faster versions of already compact and computationally inexpensive solutions. These descriptors are favorable due to the nature of the problem. Boards move through the process in a fixed position, eliminating the need for rotation invariance. Also, as stated earlier, most of the information lies in the grain patterns which are closely related to the gradients in images. U-SURF is formed using gradient information while CS-LBP is claimed by the original authors to have ”gradient like properties”.

Multiple feature vectors were calculated for each image using W subareas. The size of one subarea is $h \times w$, where h was chosen to be the height of the board in pixels to utilize the maximum amount of local information. Different subarea widths w were tested together with different amounts of subareas W. When using large subareas, the information stored inside one descriptor is mainly from grain patterns and local defects such as knots have a smaller effect, whereas small subareas concentrate on the finer detail.

Since the desired feature vector length in our approach is short, based on our tests, narrow subareas offer the best matching accuracy. The effect of w versus matching accuracy is further illustrated in Experimental results (Figure 8).

CS-LBP feature vectors are formed by comparing opposite intensity values instead of comparing a single intensity value with the center pixel, which is the original local binary pattern method (Ojala et al., 2002). Feature descriptors used in our work were formed using the method presented in (Heikkilä et al., 2009). A radius of 1 and neighborhood of 8 was used together with 2×2 subgrid and 16 bin histogram producing a feature vector with the length of 64. A 4×4 subgrid is also common but in order to keep the feature vector length short the histogram bin count would be reduced. In our tests, we obtained better matching accuracy using fewer subgrids and a larger number of histogram bins.

U-SURF features were formed in a similar manner, except for the size of the subgrid which was set to 4x4. The vector describing each subgrid contains four values making the length of the final feature vector for U-SURF also 64. A detailed explanation of the method can be found in (Bay et al., 2008).

2.3 Alignment

To ensure that the subareas are correctly matched together, alignment of the input images is required. A small offset is tolerated, as demonstrated later in the results section, meaning that sub-pixel accuracy is not needed. In order to keep the alignment process data storage space and computational complexity requirements low, a 2-D to 1-D projection is utilized (Alliney and Morandi, 1986).

The steps included in the alignment process are following:

1. A 1-D signal is formed from the image by calculating the standard deviation of each image row.
2. The spatial difference between signals is calculated using phase correlation or cross correlation.
3. The image taken at the end of the process is shifted according to the difference found.

Because we are interested in the translation in the longitudinal direction the 1-D signals are formed in an x-direction only. Multiple projection types were tested, including the minimum and the maximum values for columns as well as column sums. Due to the nature fo the material in hand, these projection strategies do not offer sufficient discriminative qualities for signal generation. Using the standard deviation for each column improved robustness considerably. An example of how the projected signal is related to the appearance of the board can be seen in Figure 6. As we can see from the figure, defects and anomalities like knots produce the highest variations to the generated signal.

The extracted 1-D vector can be used to determine horizontal displacement with both the cross correlation and the phase correlation (Stone, 2011). The signal background variations were smoothed using a low pass filtering with zero mean and unit variance normalization. The filter border effects were removed by zeroing the ends of the signal at the half length of the filter. The cross correlation can be calculated as a convolution of two signals where one of them one is reversed. With the phase correlation, the signals are Fourier transformed, the phase difference data is extracted, and the phase difference data can be turned into cross phase correlation by using an inverse Fourier transformation. The offset can be determined by finding the index of the maximum value in the correlation data. Detailed descriptions of both of the methods can be found in (Stone, 2011).

Correlation techniques offer a fast and computationally inexpensive way to carry out the alignment. They have been widely utilized in different machine vision applications for years and highly optimized mathematical frameworks have been presented for both methods (Agarwal and Cooley, 1977; Loan, 1992).

3 EXPERIMENTAL RESULTS

3.1 Test Material

The test material consisted of two sets: 1003 images taken in the beginning and 495 images taken at the end of the process. All boards were sawn from Nordic pine, *pinus sylvestris*. Images were obtained from the real production line of a sawmill. To verify the matching results, an identification number was added to every board. Image sections were cropped from boards in a way that the identification number was not visible in the matching process. There were boards with two different widths and multiple lengths. Board dimensions were not used in any way for matching. All tests presented here are Matlab simulations.

3.2 Alignment

To study the robustness of the method against board misalignment, without the proposed alignment method, the offset was varied between 0 and 250 pixels with a sample size of 100 image pairs. The graph in Figure 7 shows that the U-SURF is more sensitive to misalignment than the CS-LBP. The U-SURF matching accuracy is immediately affected, and decreases sharply after an 18 pixel offset, while CS-LBP performance stays almost unaffected until 20 pixels. The subarea width w used was 100 pixels, which roughly translates to a offset tolerance of 20% for CS-LBP. To confirm the results the test was run again using 50 pixels as a value for w. CS-LBP matching accuracy started to decline slightly after a 10 pixel offset, confirming 20% tolerance.

In order to evaluate the proposed alignment method, images were warped with a known offset for

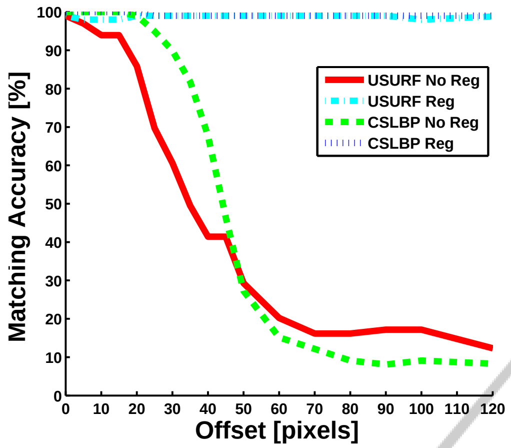

Figure 7: Matching performance with and without image alignment.

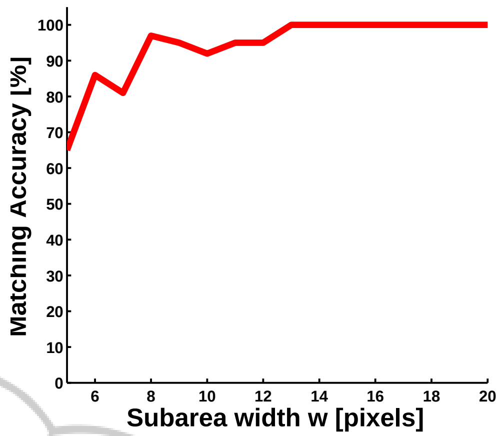

Figure 8: The effect of subarea width on matching accuracy for CS-LBP method (100 board sample size, total of 15 subwindows).

ground truth. When considering alignment within 10 pixels as an acceptable result, using the standard deviation based projection signals, the phase correlation yielded a 95.8% success rate and the cross correlation a 95.6% success rate with only a 0.2% difference. When the projection signals were formed using the minimum value of each image column, the alignment was successful in 91.8% of the cases. Using the sums of the image columns produced a correct alignment only for 64.0% of the boards. The results are summarized in Table 1.

Table 1: Successful phase correlation alignment for different projection signals. Alignment error less than 10 pixels is considered to be success.

Projection type	Acc. %
Standard deviation	95.8
Minimum column value	91.8
Column sum	64.0

3.3 Subarea Width

The subarea width w has a major effect on the matching accuracy. If there is no alignment error, the required width is small. The matching accuracy versus subarea width w is presented in Figure 8.

In this case, a width of 13 pixels was enough to produce the best possible results. In reality, w has to be set larger because of the small remaining alignment errors and a larger comparison group. The proposed alignment method typically leaves a small alignment error of 0-10 pixels. To compensate for this, and further increase the confidence of the match, a subarea width w of 50 pixels was chosen. Width of 50 pixels provides the needed tolerance of 10 pixels.

3.4 Tracing Performance

The final tracing performance depends on several factors: alignment, the number of subareas used W and subarea width w. The size of w was set to 50 pixels and the minimum required number of subareas W was searched. Performance started to decline after 15 subareas. Performance for CS-LBP features calculated from a gray scale and a gradient image as well as U-SURF features are presented in Table 2. The length of the feature vector for all of the methods was 64. For all the results presented in the table, an w of 50 and W of 15 was used.

To evaluate the confidence of the matches, a distance ratio $R_{C/I}$ was calculated by dividing the distance between the best and the second best match for correct matches, D_{12C}, with the corresponding distance for incorrect matches, D_{12I}. Also, the percentage of correct matches, for which the Euclidean distance between the best and the second best match is greater than the maximum distance in the case of an incorrect match, $D_{C>I}$, is presented.

Table 2: Tracing performance.

Method	Acc. %	$R_{C/I}$	$D_{C>I}$ %
CS-LBP	89.3	10	90
CS-LBP (gradient)	96.2	12	98
U-SURF	96.6	9	86

From the table, we can see that the overall matching accuracy for both of the descriptors is high. Using a gradient image instead of a gray scale image increased the accuracy of CS-LBP based matching considerably. While the matching accuracy of the descriptors is similar, the CS-LBP has a slightly better confidence of match.

4 CONCLUSIONS

In this paper, we presented the first machine vision based board tracing system to be used in a sawmill to track when a particular board has completed the manufacturing process. This is one important part of the chain from raw material to final products. The proposed system was evaluated using real life images and was it able to find a correct match for over 96% of the tested 495 images from a test set of 1003 images.

We proposed a projection signal based alignment method, which increased the robustness of the system considerably. Instead of using column sums, standard deviation of the column was used to create the 1-D signal. If the alignment accuracy is improved while keeping the computational complexity low, smaller subarea widths can be used, thus lowering the total number of operations required.

The use of gradient images increased the accuracy and confidence of the CS-LBP based method. One possible explanation for this is the material itself. Grain patterns are unique to different boards, similar to fingerprints. When the feature vector length was increased the benefit from gradient images started to decline, and with 256 long vectors, the matching accuracy was the same. Both of the descriptors are computationally inexpensive and they are well suited for an application where real-time performance is a critical parameter.

For future work, implementation using parallel computing needs to be considered. Accelerated methods for database queries and comparisons, as well as strategies for limiting the number of feature matrix comparisons, can offer a significant increase in the total system performance. Initial pruning of possible candidates for matching can be started in the alignment state. Also, a new ORB descriptor (Rublee et al., 2011), which is claimed by original authors to be tens of times faster than the SURF method, should be tested in this application. Fingerprint matching techniques could also be well suited for this kind of task.

The described system was targeted here to be used inside sawmills although it is not in any way limited to that application area.

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