A System for Optimal Edging and Trimming of Rough Hardwood Lumber

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Abstract

Despite the importance of improving lumber processing early in manufacturing, scanning of unplaned, green hardwood lumber has received relatively little attention in the research community. This has been due in part to the difficulty of clearly imaging fresh-cut boards whose fibrous surfaces mask many wood features. This paper describes a prototype system that scans rough, green lumber and automatically provides an optimal edging and trimming solution along with resulting lumber grades. The system obtains thickness (profile) and reflectance information at 1/16-inch (1.6-mm) resolution, using commercially available laser sources and a video camera. It analyzes the resulting images to detect wane and important lumber-degrading defects. A hierarchical defect detection scheme first analyzes the profile image for shape-based characteristics to locate wane, and to identify holes, splits, and background. Wane boundaries are detected with 3/16-inch (5-mm) error on average. The reflectance image is then assessed using a modular artificial neural network (MANN) to locate clear wood, knots, and decay. The MANN consists of a multilayer perceptron network for the detection of clear wood, and a statistically trained radial basis function network that identifies knots and decay. With this approach, we have achieved a pixel-level classification accuracy of 96.7%. Finally, a postprocessing step refines MANN output by identifying manufacturing marks that have been incorrectly classified as defects. Application software then finds optimal solutions for placement of cuts to yield maximum commercial value.

1. Introduction

In most of today's hardwood sawmills, edger and trimmer operators make a quick visual examination of each board and determine the placement of cuts based on their knowledge of lumber grades and current lumber prices. Unfortunately, several problems adversely affect their decision-making ability. First, visual estimates of board surface area and grade are subjective. Second, prices can fluctuate rapidly. Third, there exist millions of potential edging and trimming settings that must be considered. Fourth, edger operators tend to be biased toward the removal of wane beyond what is necessary by lumber grading rules. These reasons, together with such fundamental issues as operator training and fatigue, suggest that a strong need exists for an automated solution.

Losses from improper edging and trimming can be substantial. Williston [10] reported that for some mills 45% of a log's original volume is converted into chips from slab boards and from edgings. As described above, most sawmill edger operators remove an excessive amount of wood, and this can result in value losses of 30% [2]. Volume and value losses from improper trimming operations exacerbate the severity of edging losses. In a case study of 3 hardwood mills, Regalado et al. [8] found that edging and trimming operations resulted in lumber values that were only 65% of optimum. Because of the large amount of waste that occurs in current edging and trimming practices, computer-controlled optimization of edging/trimming operations is essential for increasing profits for conserving the timber raw material, and for creating primary products of high value.

This paper describes a prototype system that scans rough, green lumber and automatically provides an optimal edging and trimming solution along with resulting lumber grade. Unlike most board-scanning systems, which process planed wood, this system has been designed specifically for use with unplaned boards in the green state. In the rough state, boards commonly hold additional wood fiber, debris, dirt, and saw marks. All of these can increase the difficulty of image analysis. These difficulties are mitigated somewhat if the wood is still in a “just cut”, undried state when imaged. The additional moisture that is present immediately after log breakdown tends to produce images with higher contrast, particularly near some defect types, and this can be used to advantage during image analysis. Very little work has addressed image-related problems that are specific to rough lumber. Some early research [3-5] considered defect detection in rough lumber, but they subsequently abandoned the rough-lumber problem and looked instead at surfaced lumber. For a typical hardware sawmill layout, the new system would be placed immediately after the headrig. Early descriptions of the system appear in Lee et al. [6, 7, 18]. The remainder of this paper focuses on the problems of image acquisition, wane detection, and surface defect detection.

2. System Setup and Data Acquisition

2.1 Scanning System

Our prototype scanning system uses pinch-rollers to move boards under a video camera that is mounted vertically, looking downward as depicted in Figure 1. The camera is positioned to capture a 16-inch (0.41 m) field of view, yielding a resolution of 1/16 inch (1.6 mm) per pixel. Two side-mounted laser sources obtain reflectance information, and an additional laser source, mounted downstream of board movement, is used to measure thickness (profile) information. All three laser sources are solid-state devices, producing fan-shaped sheets of light. The system currently scans boards at 2 feet/s (0.6 m/s).

2.2 Profiling

The system uses a common technique to obtain profile images, which are use here to identify wane and voids [11]. Because of the placement of the downstream laser source, with the plane of light angled at approximately 45 degrees relative to the surface of the board, triangulation can be used to determine small variations in board thickness. Greater board thickness causes larger offsets for the bright laser curve in the image. Our system obtains thickness measurements at 1/16-inch spacing (1.6 mm), along both the width and length of each board. Because many lumber attributes, particularly voids and wane, are associated with surface irregularities, profiling is extremely useful. Some existing commercial systems use a variation of this approach to determine board edges and to guide edge saws, although those systems are not concerned with defect detection, and obtain measurements at much lower resolution lengthwise on the board. Automatic detection of incoming boards is possible by monitoring profile data, activating the system to collect profile and tracheid information.

2.3 Reflectance Imaging

Two laser sources are positioned at the sides of the camera for reflectance (brightness) imaging. Much of this light is reflected from the surface of the wood, but a portion of the light is scattered within the wood, giving a bright region around the point of incidence. The amount of internal scattering depends heavily on the physical characteristics of the wood. Known as a "tracheid effect" [9], the internal scattering takes advantage of the differential reflectance of laser light in response to grain angle and different densities on the board. While hardwoods do not contain tracheids, they do contain vessels that are smaller and fewer in number, but effect a similar phenomenon. One approach to assessing vessel-induced scatter is to compute sums of pixel intensity values in a direction perpendicular to the laser line, but not including the central laser line itself. Increased scattering can be detected in this manner and used to detect defects.

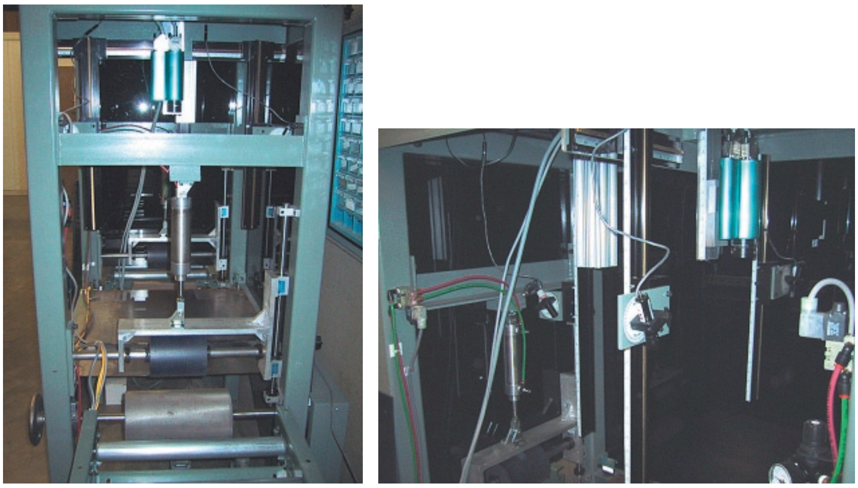


Figure 1: Scanning system (detail view).
Three laser sources provide illumination for one video camera.

3. Defect Detection and Identification

3.1 Preprocessing

Preprocessing of the acquired image prior to defect detection is essential. In our implementation, this comprises tracheid-profile registration, profile smoothing, and background removal. Because of the need for real-time operation, relatively simple steps are employed.

Registration is a fundamental task in image processing. It finds the best alignment between two or more images that are obtained at different times, from different sensors, or from different viewpoints. In our scanning system, the profile and reflectance information are taken from a moving object using different sensor rows of the camera. The collected images are therefore displaced slightly.

Profile images of rough hardwood boards suffer from various noise sources: residual bark, debris, and dust; spatial quantization of the sensor array; sampling and quantization of intensity values; thermal sensor noise; and problems in thickness estimation due to variations in surface reflectance. Residual bark and debris make it difficult to detect wane boundaries with high accuracy. Unlike other noise sources, which can be eliminated in many cases by applying smoothing filters, residual bark and debris are more resistant. In fact, because no smoothing filter can perfectly remove noise due to bark and debris from the wane area, this presents the most challenging part of the wane detection problem from profile images.

3.2 Modular Decision-Tree Approach for Defect Identification

Early attempts at defect identification did not provide satisfactory results, so we applied modular approach to tackle this problem. Typical modular methods consist of several modules of which each module is specialized for a specific task. Because the prototype scanning system collects two different images, they can be utilizable separately for different defect types. The block diagram in Figure 2 presents an overview of the modular identification system. Profile images are first analyzed to identify the background and to detect wane and void regions. Simple adaptive thresholding [12] of the profile image effectively removes the background. Wane is then identified within the remaining wood using a novel approach based on surface shape characteristics [7]. Then, voids (holes and splits) are identified by simply thresholding the remaining portion of the profile image.

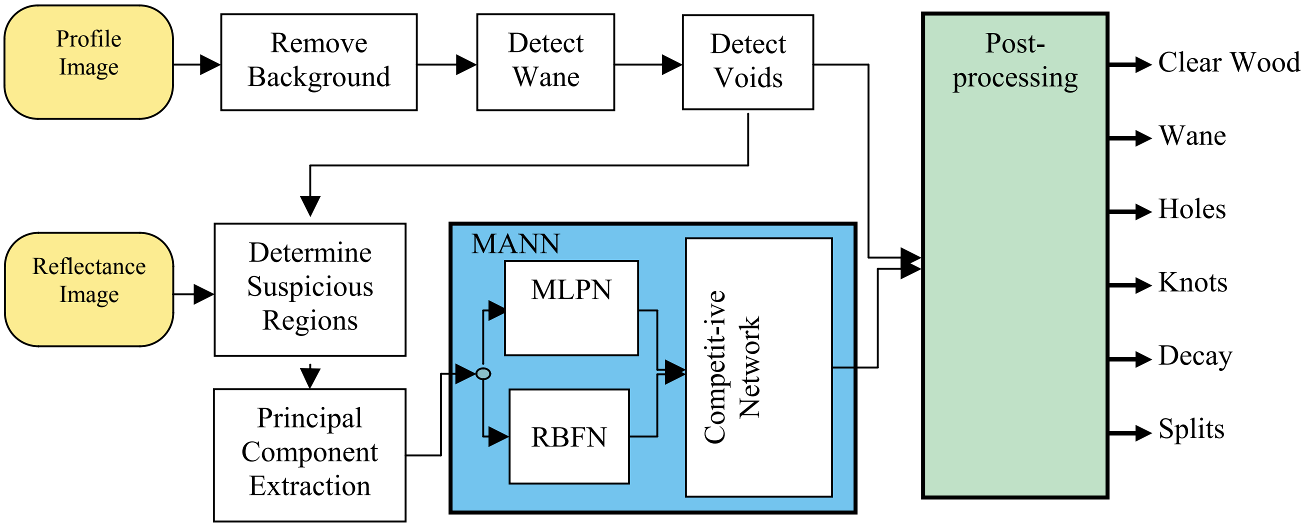


Figure 2: Block diagram for overall classification procedure. Two registered images are provided as input. The profile image is first analyzed for shape-based characteristics. The reflectance image is then assessed using a modular artificial neural network to determine the locations of clear wood, knots, and decay.

At this point, remaining unclassified regions represent the board surface that must be examined to locate any other defects. A modular artificial neural network (MANN) assigns tentative labels to each pixel using reflectance information inside the unclassified region. Within the MANN, a multi-layer perceptron network (MLPN) identifies clear (unblemished) wood; and a statistically trained radial bases function network (RBFN) labels other defects (knots and decay). A competitive decision scheme resolves the output from the two networks. To speed up the process, the MANN examines only "suspicious" regions, which are areas darker than clear wood. Finally, a post-processing step refines the MANN output, by eliminating many misclassifications, e.g., manufacturing marks that might be incorrectly labeled as defects.

The first task is to remove background that is not related to the actual wood area. Instead of using a fixed limit for thresholding, we implemented Otsu's threshold selection method [12] to threshold the profile image and effectively removed the background.

Wane detection, at first glance, seems to be a simple problem that requires only the selection of a threshold thickness for each board. However, for several reasons including additional bark and debris that is present on rough boards, we found that simple thresholding is not adequate for determining wane regions in profile images. For an accurate determination of wane boundary in the presence of bark and debris, the system utilizes surface properties such as orientation and curvature along with a set of criteria representing the characteristics of wane boundary. As described in [7], the system finds local quadratic fits to profile data, and uses this to compute curvature and surface-normals. Related analyses can be found in [14, 15].

After background removal and wane detection, only the board surface remains. For the surface, profile information is examined again to determine where splits and holes lie. A simple thresholding operation, applied only to the board surface, is fast and reliable for void detection. Then shape analysis is used to identify split and hole regions. Geometric assumptions are used, including the expectations that holes are round and splits are narrow in shape. At this stage of classification, only the non-wane board surface that is free of voids remains for defect identification.

Because the dominant portion of each board is clear wood, feeding data from those regions into a defect classifier wastes considerable processing time and should be avoided if possible. Typically, clear wood regions are fairly different in reflectance values from defect regions, so a carefully selected threshold can eliminate clear wood region from further classification. Because clear wood constitutes most of each board, an average reflectance value for the board will correspond closely to clear wood, and serves as a reasonable threshold for eliminating clear wood. The threshold value is set based on the statistical mean and standard deviation. Only the part of a board below this threshold value, called a "suspicious" region, is fed into the MANN, eliminating a substantial amount of classification effort.

Principal component analysis (PCA) is an efficient method for dimensionality reduction of an input data set without a significant loss of information. It performs an eigen-analysis on a covariance matrix of sample data, and creates a transform matrix by choosing eigenvectors corresponding to eigenvalues greater than a certain value. The transform matrix converts a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called *principal components*. The artificial neural networks (ANNs) described in the next section use texture information from a reflectance image as input. Data are taken from a small window of size 7×7 placed at a location that is targeted for classification. However, the texture information stored in this input vector is highly correlated and it is possible to reduce its dimensionality with PCA. This reduces the size of the ANNs, resulting in faster classification. The scanning system selects only 24 principal components out of 49 dimensions.

In [16], Jacobs et al. described several advantages that a modular network possesses over a single ANN in terms of learning speed, representation capability, and the ability to deal with hardware constraints. If the input space is complex or has a mixture of features from different classes, a modular network is often able to learn faster than a single network because each module responds to a single class. In our classification problem, early experimental results showed that a traditional MLPN often resulted in unsatisfactory classification performance. Similarly, the use of a single RBFN to classify all defects along with clear wood required an exorbitant number of RBFN nodes in the hidden layer. Therefore, we decided to subdivide the classification problem so that one network distinguishes clear wood from defects, and a second network considers defects only. We selected a small MLPN for clear wood classification, using only a small number of nodes in the hidden layer. Due to the complexity of the latter problem, we decided to use an RBFN to distinguish knots from decay. For both networks, careful consideration was given to the number of nodes in the hidden layer.

In most RBFN applications, the primary concerns are to determine the kernel function and to select a reasonable number of nodes. A common approach is to select one node per training sample, and then focus on the selection of kernel function parameters [17]. However, this can result in prohibitive computational costs when the training set is large. On the other hand, if the number of nodes is reduced excessively, then classification performance can degrade to unacceptable levels. We have developed a new approach that uses a clustering approach to select the number of nodes and that performs an optimization step to select RBF parameters. Details of the approach can be found in [6].

A post-processing step refines MANN output by correcting manufacturing marks that have been incorrectly classified as defects. These marks appear as narrow vertical (edge to edge) discolorations caused by mineral oxidation or by metal deposition from conveyors or side chains. Elliptic shape approximation is applied to each classified defect in order to identify vertical strips. Also, the post-processing step resolves any uncertainty between holes and splits.

4. Edging/Trimming Software

After all board defects have been identified, data describing each defect and the board outline are recorded as ASCII text and passed to the application software, which searches for the best edging and trimming solution. In [13], Schmoldt et al. demonstrated that this search algorithm, a branch-and-bound method, is superior in speed and accuracy to any other current edging/trimming software. In the branch-and-bound approach, the solution space is partitioned into four subsets (corresponding to the inward movement of the two edge lines and two trim lines), in a top down tree structure. Each of these subsets (subtrees) can be further partitioned as needed. For most boards only a few tree nodes are actually examined, most of the searching effort is consumed in generating the nodes themselves.

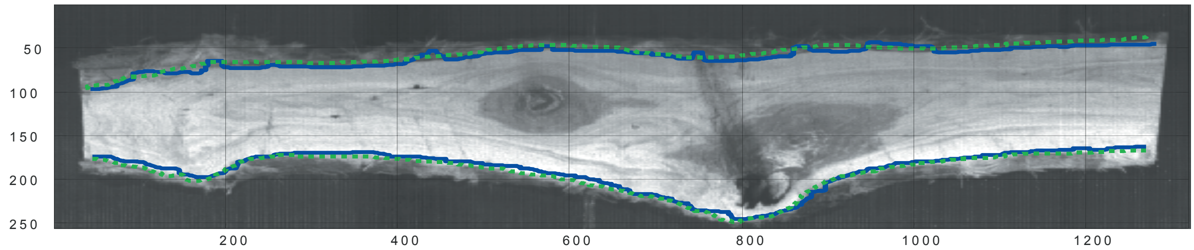
5. Experimental Results

Wane boundaries were manually delineated for two profile images. These ground-truth boundaries were compared to output from the wane detection method. One of the experiments is shown in Figure 3 and its statistical results are summarized in Table 1. Dotted lines in Figure 3a show the ground truth for the upper and lower wane boundaries, and the detected wane boundaries are depicted with solid lines. Figure 3b shows the absolute difference (in pixels) between the ground truth and the detected wane boundaries. Note that debris and residual bark, which are particularly apparent near columns 100 and 1000 for the upper part of the board, severely affected detection accuracy. Erroneous profiling also arises from laser intensity variation, which creates uneven profile information for level surfaces. This unevenness causes slightly higher average errors for the bottom edges (Table 1). Outliers are defined as detected wane boundaries that deviate more than 8 pixels (12.7 mm) from the ground truth boundary.

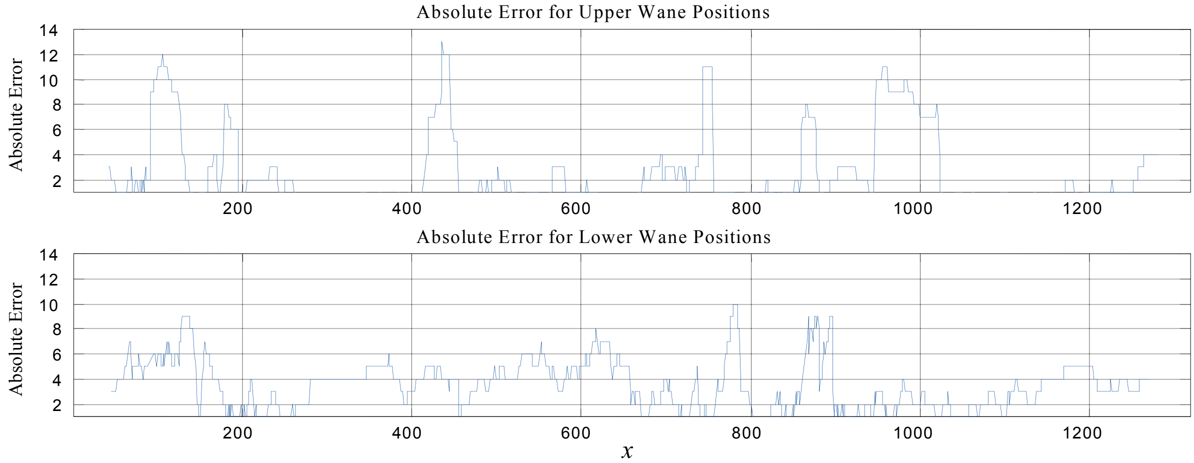
Table 2 shows the performance of three different network topologies to classify clear wood, knots, and decay. Our MANN approach exhibits superior performance over single networks, RBFN and MLPN. We used 10-fold cross-validation to measure the performance in each case.

Table 3 and Figure 4 show scanning system results, where solid red lines indicate edging/trimming solutions. In the first example, a red oak board (Figure 4a) contains a substantial amount of wane but few defects. It is graded as #1 Common valued at $2.34 (USD). For experimental purposes, we picked several low quality boards (Figure 4b-c) that contain many manufacturing marks. These marks originate from delayed chemical oxidizing of saw metal or from metal and dirt rubbing off of conveyors and other materials handling equipment. Nevertheless, the systems must deal with these anomolies. Our classification software largely ignores these marks, while identifying actual defects, but the system still needs to be improved, as shown on the right side of example OR005 (Figure 4b) and lower part of example OR008 (Figure 4c).

The scanning system is controlled and operated by a 360 MHz Pentium II PC with 128MB memory. It has scanned 86 boards while testing its functional software components for classification and optimization. Classification and grading take up to 20 seconds depending on the number of defects contained in the board, and current scanning speed is set to 2 feet/second. Although varying the scanning speed is possible, it requires reconfiguration of the imaging camera, which will affect image quality. A normalization technique could be used to reduce image quality impacts for different configurations, but it is not feasible for the current system due internal electrical noise limitations of the imaging camera.



(a)



(b)

Figure 3: Error analysis for sample board 1. (a) Dotted curve: true wane position. Solid curve: estimated wane position. (b) Absolute error for upper and lower edges of the board. For the upper edge, residual bark and debris cause several large deviations. For the lower edge, variations in reflected laser intensity are a major sources of error.

Table 1. Error analysis for the wane detection method. Statistics for absolute error are given separately for the "upper" and "lower" edges of two unplaned boards. Average and standard deviation values are given in units of pixels, where each pixel represents 1.6 mm (1/16 inch).

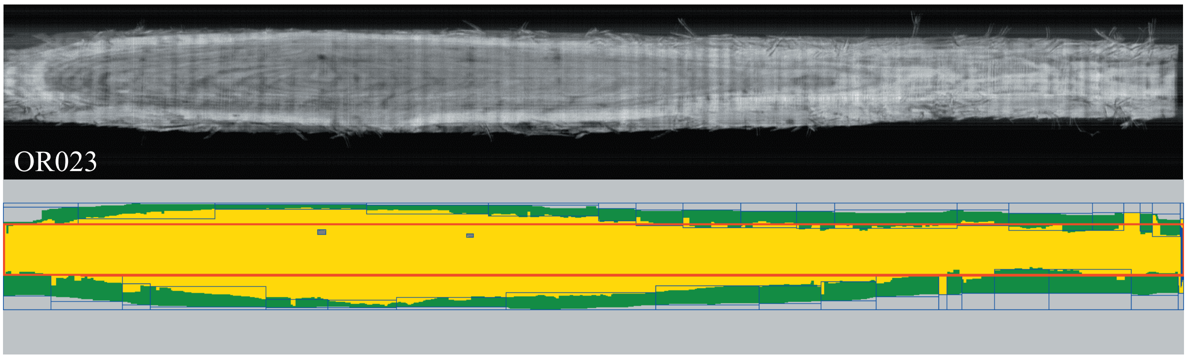
Surface Approximation Method	Sample Board 1		Sample Board 2	
	Upper	Lower	Upper	Lower
Average (pixel)	2.3	3.5	1.6	2.0
Std. Dev. (pixel)	3.0	2.0	1.4	2.9
Outlier (%)	8.1	2.1	0.007	6.3

Table 2. Performance comparison for various network topologies. There are 95 samples in each fold.

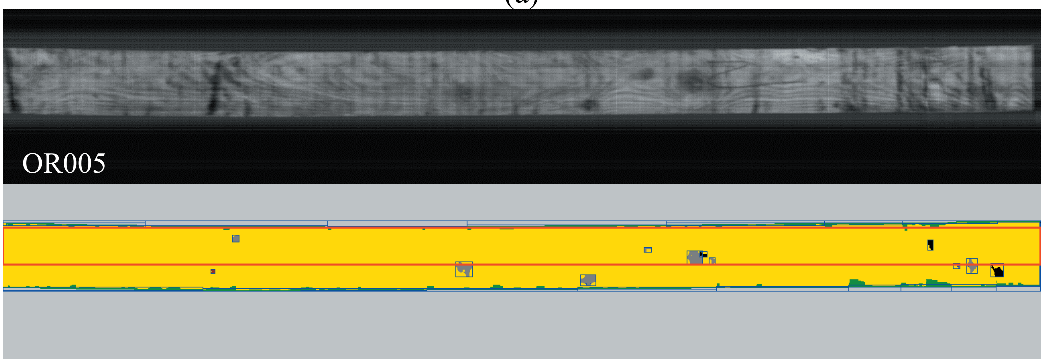
Network Type	Fold Number										Avg.	Accuracy
	1	2	3	4	5	6	7	8	9	10		
MANN	87	90	94	91	89	91	95	95	95	92	91.9	96.7%
RBFN	82	84	87	89	85	89	91	92	90	92	88.1	92.7%
MLPN	81	82	88	87	86	85	90	91	87	89	86.6	91.2%

Table 3. Summary of edging and trimming results for four example boards. (Three of these boards are shown in Figure 4.)

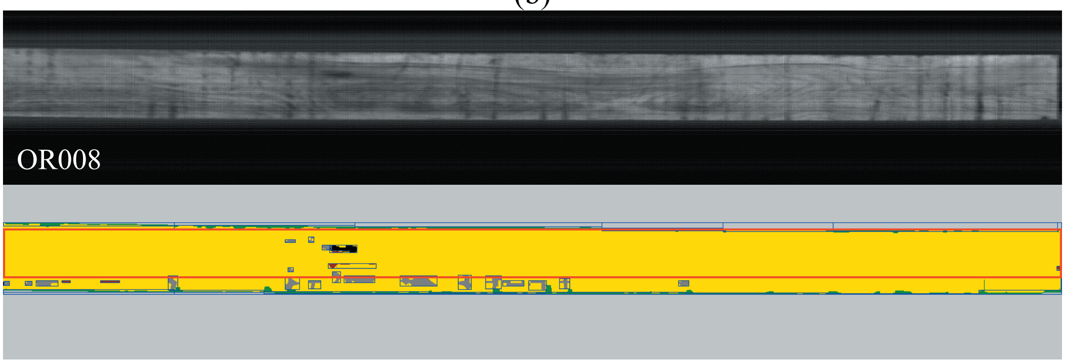
	Board ID			
	OR023	**OR005**	**OR001**	**OR008**
Size (Before Cut)	108"L x 9.75"W	95"L x 6.44"W	96.5"L x 7.38"W	97"L x 6.56"W
Size (After Cut)	108"L x 4.5"W	95"L x 3.25"W	96.5"L x 6.75"W	97"L x 4.5"W
Grade	#1C	#3C	#2C	#1C
Value (USD)	$2.34	$0.77	$1.84	$2.34



(a)



(b)



(c)

Figure 4: Three experimental results. The examples show that our classification software works well on typical situations in rough lumber, and that manufacturing marks are ignored while actual defects are labeled. Post-processing still needs improvement because there are some false classifications on the right side of example OR005 and the lower part of example OR008.

6. Conclusions

The potential exists for dramatic efficiency improvements in hardwood sawmill operations, made possible by recent technological advances in imaging and computing technology. This paper has described a prototype system that partially addresses the problem of selecting optimal edging and trimming solutions. We have developed an integrated system of materials-handling hardware, image-acquisition hardware, image-analysis software for detecting wane, knots, decay, and voids in rough lumber, and software to make optimal edging/trimming decisions. Knowledge of the locations of these lumber-degrading features, along with knowledge of grading rules and current market prices, are needed for the selection of optimum saw positions.

The reason for targeting rough, unplaned lumber is that high-speed, computer-aided decisions made earlier in the production chain offer the greatest potential for economic gain. Rough lumber poses unique problems, however, because of the presence of fiber strands and saw marks that are not typically present after planing. This creates difficulties for defect recognition.

The scanning system uses a commercially available "smart camera" system, the MAPP 2200 [1], for image capture. This camera is unique in that it contains an on-board programmable processor to perform image processing operations in parallel with image capture. Low-cost solid-state lasers are used as illumination sources. These have been located in an effort to exploit the reflectance effect, in which light scatters within the fibrous material of the wood before being imaged. A standard PC serves as the host processor. The prototype system is relatively small, and can be moved into sawmills without extensive modification of existing facilities.

Technological advances of the past few years have made this prototype system feasible at a relatively low cost. Ultimately, such a system will significantly improve the utilization of hardwoods by improving the quality of sawmill output and by reducing waste. A companion benefit is that each board processed by such a system will have a consistent computer grade, with less variation than is possible with human graders.

Acknowledgments

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