A Prototype Scanning System for Optimal Edging and Trimming of Rough Hardwood Lumber

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Abstract

This paper is concerned with scanning and assessment of hardwood lumber early in the manufacturing process. Scanning operations that take place immediately after the headrig have significantly greater potential to reduce loss and improve economic value, as compared to scanning that is performed during subsequent manufacturing steps. In spite of this, the scanning of green, unplaned lumber has received relatively little attention in the research community. Part of the reason for this is that image capture and analysis are more difficult when fibrous structures and debris are present near the surface of the wood. This paper describes a prototype system that addresses this problem. The system, which automatically provides an optimal edging and trimming solution along with resulting lumber grades, has been has been developed and tested for use with unplaned hardwood lumber that is still in the green state. 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. Wane boundaries are detected with 3/16-inch (5-mm) error on average, and a modular artificial neural network is used to locate clear wood, knots, and decay. Using this surface information for each board, the system then automatically finds optimal solutions for placement of cuts to yield maximum commercial value based on current market prices.

Introduction

Most of today's hardwood sawmills rely heavily on visual examination of lumber by human operators. Edger and trimmer operators, in particular, typically make quick visual examinations of each board in order to determine the placement of cuts. These decisions are based on their estimates of board surface area, the placement of wane and defects, knowledge of lumber grades, and knowledge of current lumber prices. Unfortunately, such visual assessments are quite subjective. Issues such as operator training and fatigue exacerbate the problem. These considerations suggest a strong need for an automated approach to edging and trimming operations.

Losses from improper edging and trimming can be substantial. For example, edger operators tend to be biased toward the removal of an excessive amount of wood, and the resulting level of value losses has been estimated at 30% [2]. Another study [11] found that for some mills 45% of a log's original volume is converted into chips from slab boards and from edgings. 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, 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 scanned very soon after the headrig. 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.

The remainder of this paper focuses on the problems of image acquisition, wane and defect detection, and the optimization of edging and trimming settings. Earlier descriptions of our work appear in Lee et al. [4 - 7].

Data Acquisition System

Our prototype scanning system uses pinch-rollers to move boards under a video camera that is mounted vertically, looking downward as depicted in **Error! Reference source not found..** The camera is positioned to capture a 16-inch-wide field of view, yielding a resolution of 1/16 inch 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 approximately 2 feet per second.

The system uses a common technique to obtain profile images, which are used here to identify wane and voids. 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 along both the width and length of each board. Profiling can be used very effectively to detect voids and wane. 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 most of those systems 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.

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" [10], 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.

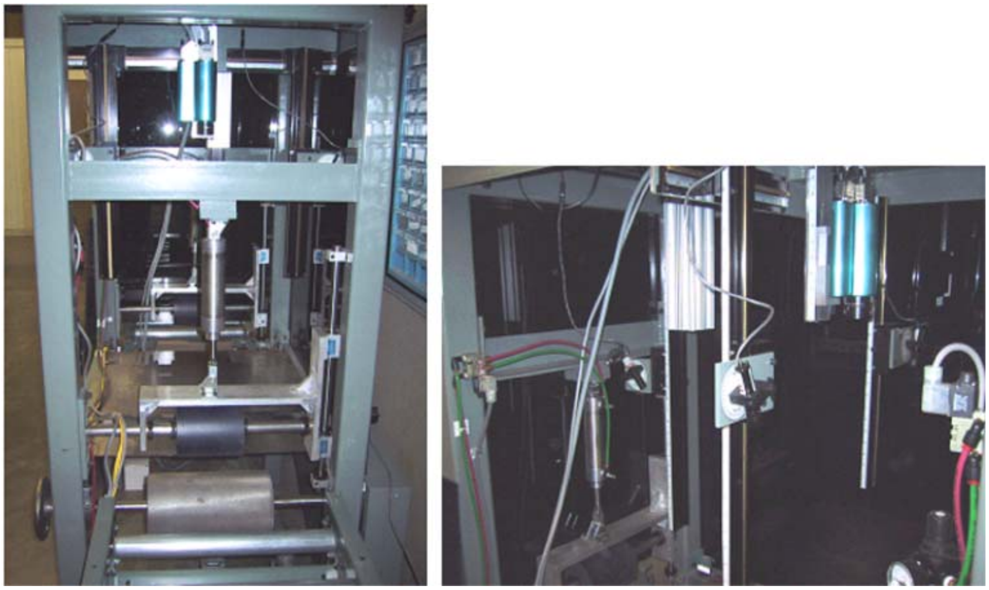


Figure 1. Scanning system (detail view). Three laser sources provide illumination for one video camera.

Defect and Wane Detection

Preprocessing of the acquired image prior to defect detection is needed for several purposes. In our implementation, preprocessing is used for tracheid-profile registration, profile smoothing, noise suppression, 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.

We employ a modular approach to defect detection. Typical methods consist of several modules of which each is specialized for a specific task. The block diagram in Figure 1 presents an overview of the modular identification system. Because the scanning system collects two different image types, they can be processed in different ways for different defect types. Profile images are first analyzed to identify the background and to detect wane and void regions. Simple adaptive thresholding of the profile image is used to distinguish the wood surface from the background. Wane is then identified within the remaining wood using a novel approach based on surface shape characteristics [6]. Voids (holes and splits) are then identified by simply thresholding the remaining portion of the profile image.

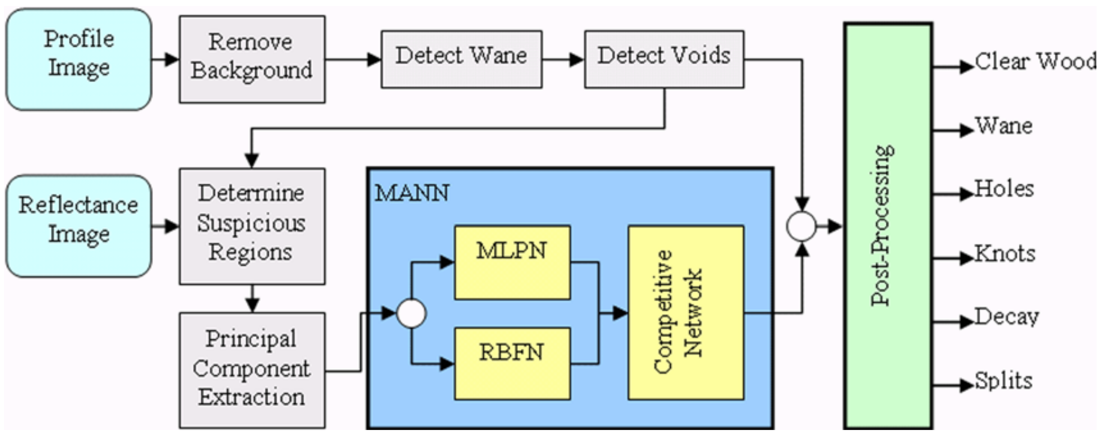


Figure 1. Block diagram for overall classification procedure. Two registered images are provided as input. The profile image is first analyzed for shape-based characteristics. The reflectance image is then assessed using a modular artificial neural network to determine the locations of clear wood, knots, 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-basis-function network (RBFN) identifies 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, such as saw marks that might be incorrectly labeled as defects.

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 improved determination of wane boundary in the presence of bark and debris, the system utilizes surface properties such as surface curvature. As described in [6], the system finds local quadratic fits to profile data, and uses this to compute curvature and then to determine wane boundaries.

After background removal and wane detection, only the board surface remains. Profile information is examined again to determine the locations of splits and holes. A simple thresholding operation, applied only to the board surface, is fast and reliable for this purpose. Shape-based analysis is then 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 to be processed 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 much of the clear wood from further consideration. 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 portions of a board that are below this threshold value considered "suspicious," and are fed into the MANN.

The artificial neural networks employed in the system use texture information from the reflectance image as input. Data points are taken from small windows of size 7×7, centered at locations that are targeted for classification. Jacobs et al. [3] describe several advantages that a modular network possesses over a single, traditional ANN in terms of learning speed, representation capability, and the ability to deal with hardware constraints. If the input space contains a mixture of features from different classes, a modular network is often able to perform better 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.

No artificial neural network can be expected to produce perfect output for all situations. For this reason, we added a post-processing step that refines the MANN output. One refinement is the correction of 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 uncertainty between holes and splits.

Edging/Trimming Software

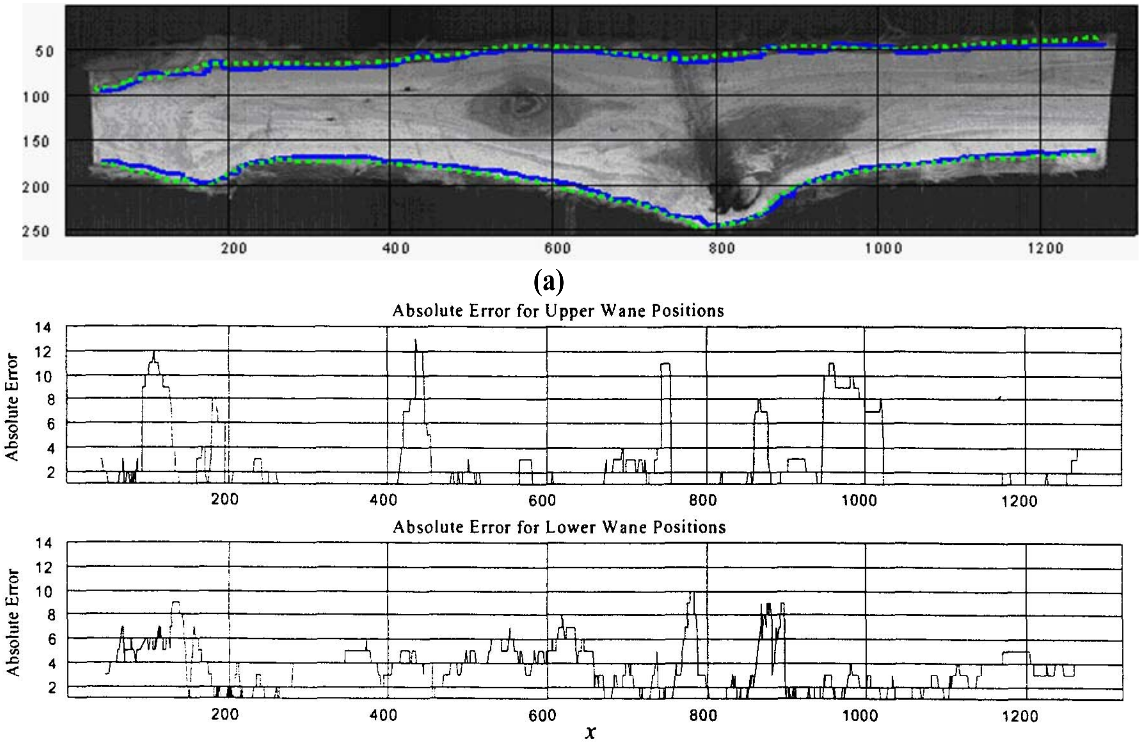
After board defects have been identified, descriptions of the board's dimensions and of each defect are passed to a software module [9] that searches for optimum edging and trimming positions for the board. This module uses a branch-and-bound search procedure that is much more efficient than exhaustive search. Inward movements of the two edge lines and two trim lines are considered in succession.

Experimental Results

Wane boundaries were manually delineated for two profile images. These ground-truth boundaries were compared to output from the wane detection method. The result of one experiment is shown in **Error! Reference source not found.** and its statistical results are summarized in Table 1. Dotted lines in **Error! Reference source not found.a** show the ground truth for the upper and lower wane boundaries, and the detected wane boundaries are depicted with solid lines. **Error! Reference source not found.b** 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 2 show scanning system results, where solid lines indicate edging/trimming solutions. In the first example, a red oak board (Figure 2a) contains a substantial amount of wane but few defects. It is graded as #1 Common and valued at $2.34 (US). For experimental purposes, we picked several low quality boards (Figure 2b-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 2b) and lower part of example OR008 (Figure 2c).

The scanning system is controlled and operated by a 360 MHz Pentium II PC with 128MB memory. In one test of, it scanned 86 boards and the results were analyzed. Current scanning speed is approximately 2 feet/second, and classification and grading may take up to 20 seconds depending on the number of defects contained in the board. 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 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** 1	2	3	4	5	6	7	8	9	10	**Avg.**	**Accuracy**
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 2.)

	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

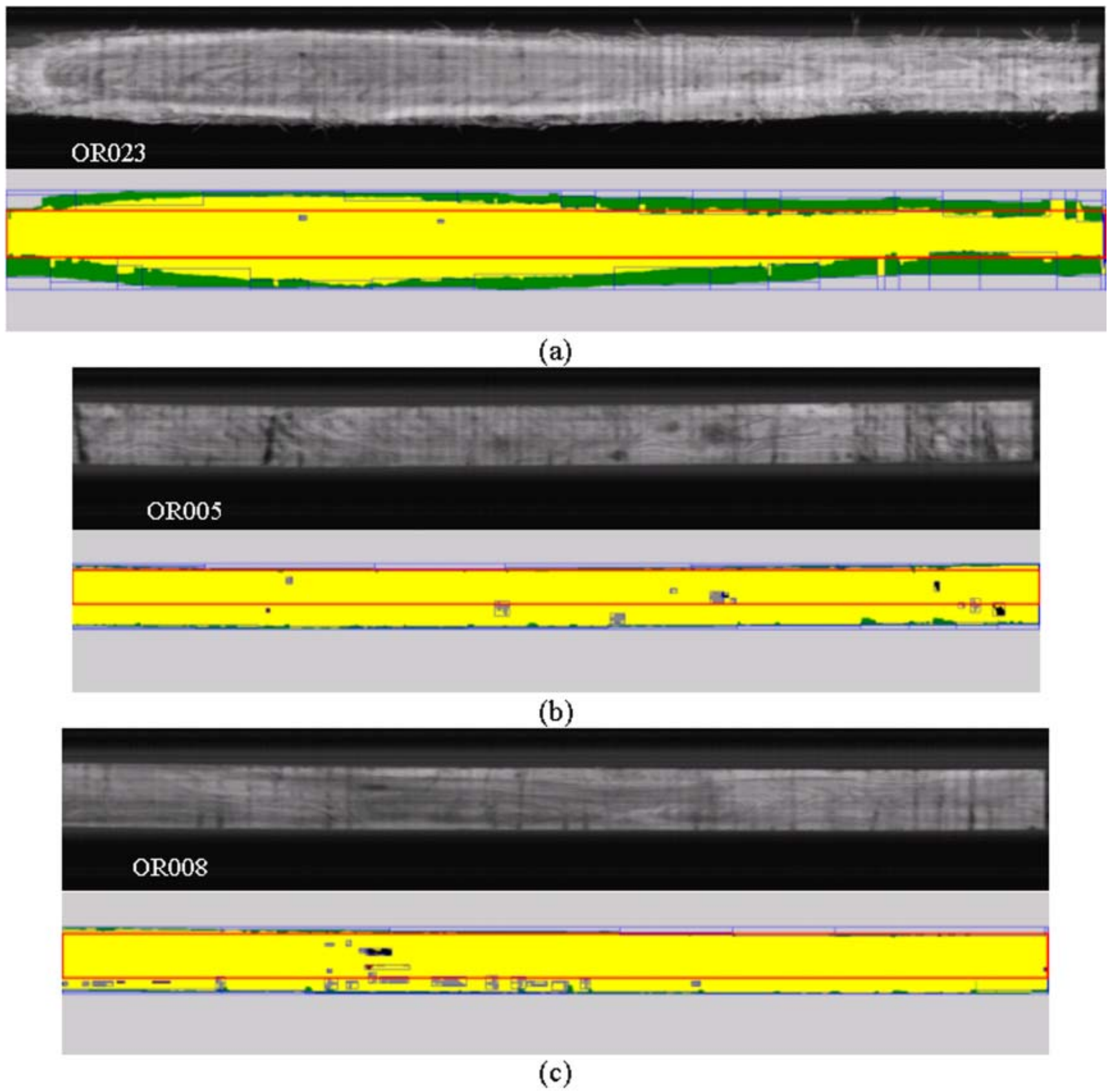


Figure 2. Example experimental results. The examples show that our classification software works well on typical situations in rough lumber, and that most manufacturing marks are ignored while actual defects are labeled. Post-processing still needs improvement because there are some false classifications on the right side of(b) and on the lower part of (c).

Conclusions

Recent technological advances in imaging and computing technology have raised the potential for dramatic efficiency improvements in hardwood sawmill operations. 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, and edging/trimming software. Knowledge of the locations of lumber-degrading features, along with knowledge of grading rules and current market prices, are needed for the selection of near-optimal edging and trimming 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 wane detection and defect identification.

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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