Evaluation of a Multi-Sensor Machine Vision System for Automated Hardwood Lumber Grading

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Abstract

Over the last 10 years, scientists at the Thomas M. Brooks Forest Products Center, the Bradley Department of Electrical Engineering, and the USDA Forest Service have been working on lumber scanning systems that can accurately locate and identify defects in hardwood lumber. Current R&D efforts are targeted toward developing automated lumber grading technologies. The objective of this work is to evaluate hardwood lumber grading accuracy based on current state-of-the-art multiple sensor scanning technology which uses laser profile detectors, color cameras, and an x-ray scanner. 89 red oak boards were scanned and graded using Virginia Tech's multiple sensor scanning system. A certified National Hardwood Lumber Association (NHLA) employed lumber inspector then graded the lumber and the boards were manually digitized and mapped for defects.

The lumber grading system was found to be 63 percent accurate in classifying board grade on a board-by-board basis. While this accuracy may seem low, the automated lumber grading system was found to be 31 percent more accurate than the line graders. Further, the automated lumber grading system estimated the lumber value to be within 6 percent of the NHLA certified value whereas the line grader overestimated the lumber value by close to 20 percent. Most automated lumber grading discrepancies resulted from board geometry related issues (e.g. board crook, surface measure rounding, calculation of cutting units, etc.). Concerning the multiple sensor scanning system, defect recognition improvements should focus on better methods to differentiate surface discoloration from critical grading defects. These results will help guide the development of future scanning hardware and image processing software to more accurately identify lumber grading features.

Keywords: Lumber Grading, Multiple-Sensor Scanning, Fuzzy Logic

Introduction

Within the next few years, the lumber manufacturing industry will see some of the first installations of automatic lumber grading systems. These grading systems will include complex mechanisms including cameras, lights, lasers, x-rays, computers, electronics and other devices necessary to identify lumber grading features. Sophisticated computer software will be needed to process the volume of information generated by the scanning hardware. The resulting "digital map" of lumber defect data outputted by the software will be used to automatically sort and grade lumber according to standard grading rules (e.g. 1998 NHLA hardwood lumber grading rules). However, this data can also provide a potential wealth of information to dramatically reduce costs and increase value recovery by creating a more intelligent, more adaptable manufacturing system.

To automate lumber grading, the industry now recognizes that a multiple sensor approach to scanning must be used to get the required accuracy, consistency, and repeatability. There are three main categories into which lumber-grading features may be classified. These are: 1) visual surface features (e.g. knots, holes, splits, decay, discoloration, slope-of-grain), 2) geometry features (e.g., 3-D shape, warp, wane, thickness variations), and 3) internal features (e.g., internal voids, internal knots, decay, compression/tension wood). Most of these features are treated as defects in lumber grading and need to be removed in manufacturing processes.

Recognizing that all grading features cannot be consistently detected with one single sensing mechanism, current R&D efforts have focused on developing lumber scanning systems that combine 2 or more of these sensing modalities. Many years of industrial experience with some sensors such as black and white or color cameras have resulted in fast, robust, and inexpensive sensing systems. Some of the more recently introduced sensing technologies such as x-rays, microwave, and ultrasound are typically developed first for an application (e.g., medical industry) where speed, cost, and harsh environment are not critical factors. Several years of experience with such sensing systems will be needed before they are reliable and robust enough for lumber manufacturing and grading applications.

Virginia Tech and the Southern Research Station of the USDA Forest Service have jointly developed and refined a multiple-sensor lumber scanning prototype (Conners, et al. 1997; Kline, et al. 1997; Kline et al. 1998) to demonstrate and test applicable scanning technologies. This R&D effort has led to a patented wood color and grain sorting system (Conners and Lu 1998) and a patented defect detection system for lumber (Conners et al. 1999). The objective of this study is to test the application of this defect detection system on hardwood lumber grading. We will discuss some of our findings to date and discuss what implications they have in the development of automatic hardwood lumber grading systems.

Background

Scanning Hardware

To explore a number of wood products processing problems, recent research efforts have gone into developing a full-scale multiple sensor machine vision prototype. The system employs a color camera system, a laser-based ranging system and an x-ray scanner (see Figure 1). A new computer vision system has been developed for the prototype that uses data from all these sensors. To meet the needs of multiple sensor data acquisition and image processing, special purpose hardware was also developed and incorporated into the prototype (Drayer, 1997; King, 1998; LaCasse, 2000). This hardware has proven itself effective on a variety of machine vision applications. The full-scale machine vision prototype is unique because several different sensing modalities can be tested on full-sized lumber at industrial speeds. The prototype has been used to study a number of primary and secondary hardwood manufacturing applications including automatic sawmill edging and trimming, automatic lumber grading, automatic color sorting, and rough mill automation (Araman et al., 1992; Conners et al., 1992; Kline et al. 1998).

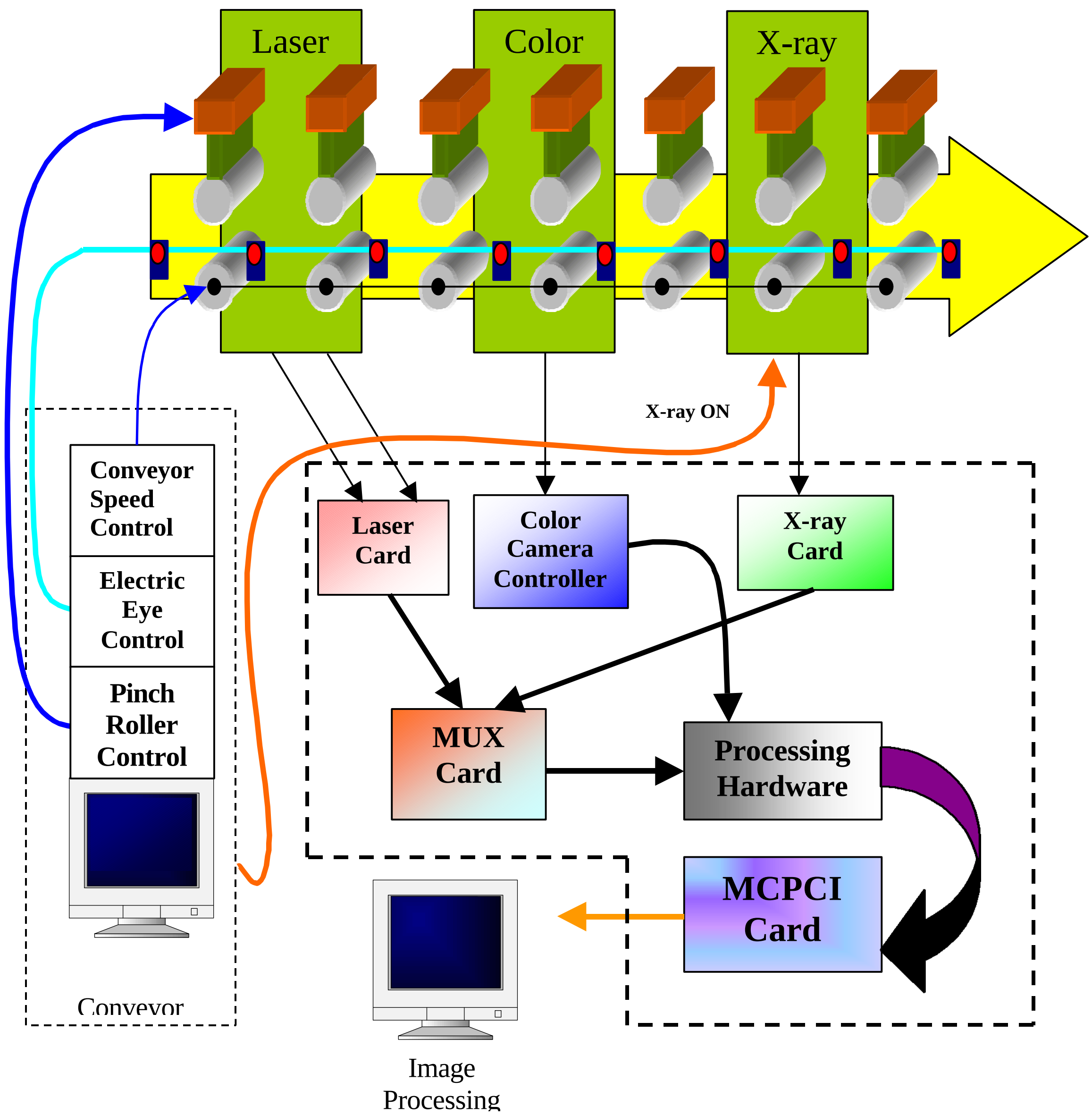

Figure 1. *The multiple sensor lumber scanning system hardware allows for the collection of 6 channels of registered image data: 1) range, 2) red, 3) green, 4) blue, 5) black & white, and 6) x-ray. Each of these channels of image data are processed in real-time using special purpose image processing hardware. A special purpose PCI interface card transfers the data to computer memory for further processing.*

Image Processing Software

The prototype machine vision system developed in this research is responsible for processing the six channels of image data (laser range, x-ray, and color which consists of red, green, blue, and black & white channels) to locate and identify defects that can be seen from the scanned lumber face. The final output of the machine vision system is a "defect map" that includes the size location, and type of every defect. The machine vision software developed in this research uses a novel data fusion approach to first preprocess the images, segment the image into regions of interest, and then employs fuzzy logic to determine which defect class the various regions belong. The machine vision software architecture consists of three major processing modules: 1) laser image analyzing module, 2) X-ray image processing module, and 3) color image analyzing module (see Figure 2).

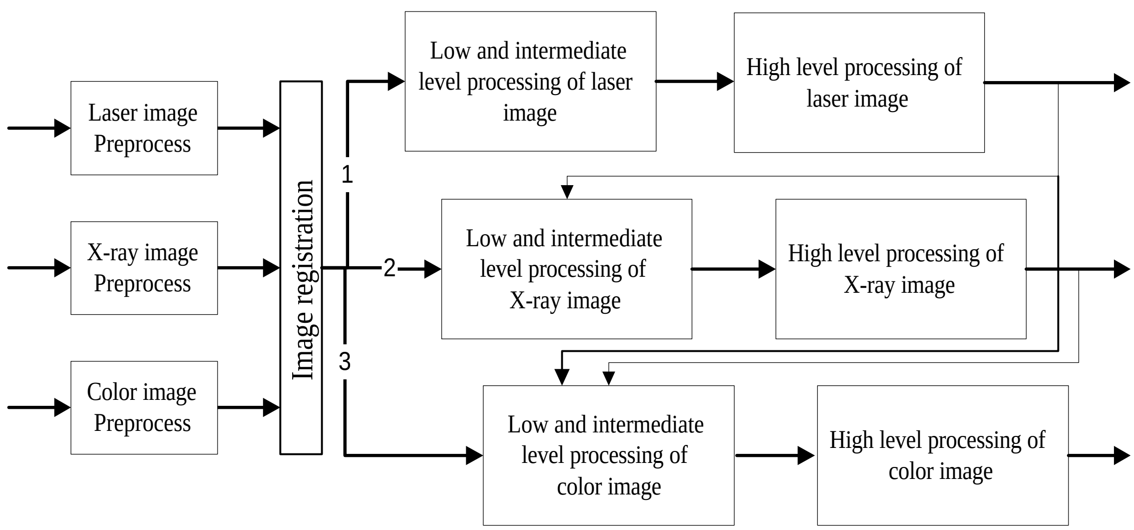

Figure 2. *Preprocessing, low-level, intermediate-level and high-level operations are applied to the image data. The output of the laser range image operations result in lumber geometry defect classifications. The output of the x-ray image operations result in internal defect classifications. The output of the color image (e.g. red, green, blue, and black & white) operations result in surface defect classifications.*

Basic Image Processing Operations

<u>Preprocessing</u>

The purpose of image preprocessing is to provide higher quality images to the computer vision system and reduce the time required to perform the image analysis. The image preprocessing employed by this system includes the following operations: shading correction, background extraction, histogram extraction, image registration and other filtering. Shading correction is applied to compensate for nonuniformities in the image collection sensor arrays. Background extraction is used to detect the lumber edge in each of the three images. Histogram extraction generate histograms for subsequent image thresholding operations.

Image registration is also treated as a preprocessing operation. Image registration generally refers to any of the methods (e.g., geometrical transformations) used to make the images from each sensor commensurate in both its spatial dimensions. That is, for instance, pixel $C_{i,j}$ in color image, pixel $L_{i,j}$ in the laser range image and pixel $X_{i,j}$ in the x-ray image refer to the same location (i, j) on the lumber surface. In this system, the image edges are used as the corresponding reference objects for image registration.

Low and Intermediate Processing

Low and intermediate processing consists of low-level segmentation, connected component region labeling, and intermediate-level region feature extraction operations. Multiple thresholding operation is performed on all to segment clear wood from possible defect regions. For example Figure 3 shows a typical histogram of an X-ray image has one large peak that represents the clear wood area and two smaller peaks. The smaller peak on the right of the large peak represents areas that have a lower density. Similarly, the smaller peak on left of the large peak represents areas that have a higher density. The inflection points can be used as to find the threshold levels to separate pixels representing areas of clear wood with normal density from pixels that might be in defect areas.

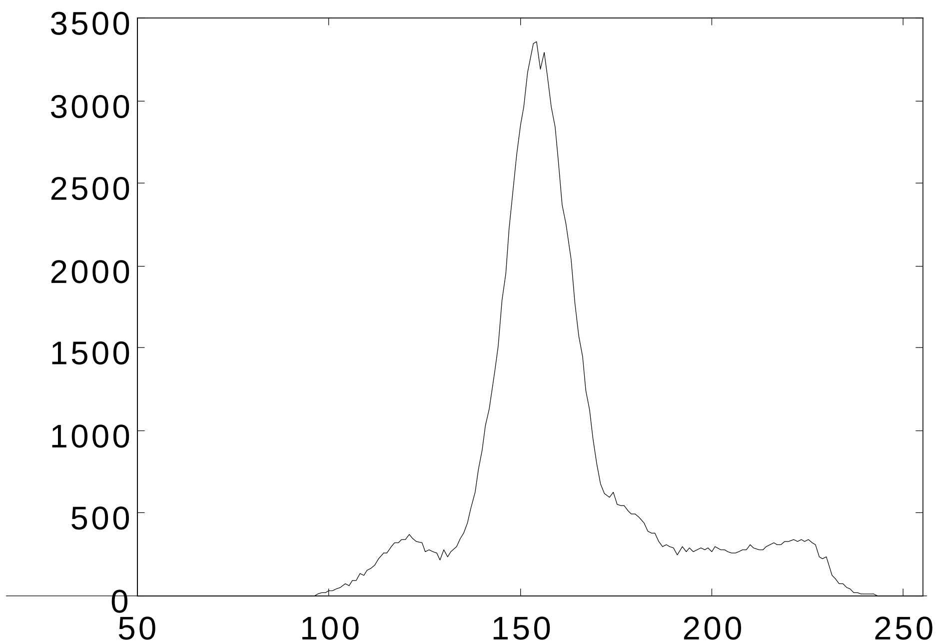

Figure 3. *An x-ray image histogram. Inflection points between peaks are used to select multiple threshold levels for the image.*

A connected component labeling operation is applied to the thresholded image to form regions that contain possible defects. A 4-neighbor connected component region labeling algorithm has been developed in this system to extract regions from the multiple thresholded image. Similar adjacent regions (e.g. within 1 or 2 pixels) are merged if certain region properties match (e.g. average gray-level intensity). Small disjoint regions (e.g., 1 or 2 pixels regions) are considered to be noise and are eliminated.

At the intermediate level processing, basic region properties such as area, shape, average gray levels, etc. are then extracted. It is important to note that six channels of image information provide a rich source of data to extract region properties that minimize ambiguities in defect classification. Region properties are the basis for classifying the various regions to a particular grading defect during high-level processing operations.

High-Level Processing

High-level processing operations are responsible for identifying which defect class is assigned to a candidate region found in low- and intermediate-level processing (see Figure 4). A number of lumber defect identification rules have been developed in this system . Each of these rules is designed to identify a particular defect class with a fuzzy logic approach. A region is sent to every rule that returns a similarity measure (approaching degree) between the region and a specific defect class. The final decision is made based on the maximum value of this measure. The region is identified as the defect class for which the value of approaching degree is the largest and the value is greater than a threshold value (e.g., 0.5). If all values of approaching degree are smaller than a specified threshold, then the region is considered to be clear wood. All results are subsequently passed to a post-processing module, which merge overlapping defects and filter defect information based on user preferences (e.g. specify if mineral streak is considered a grading defect or not).

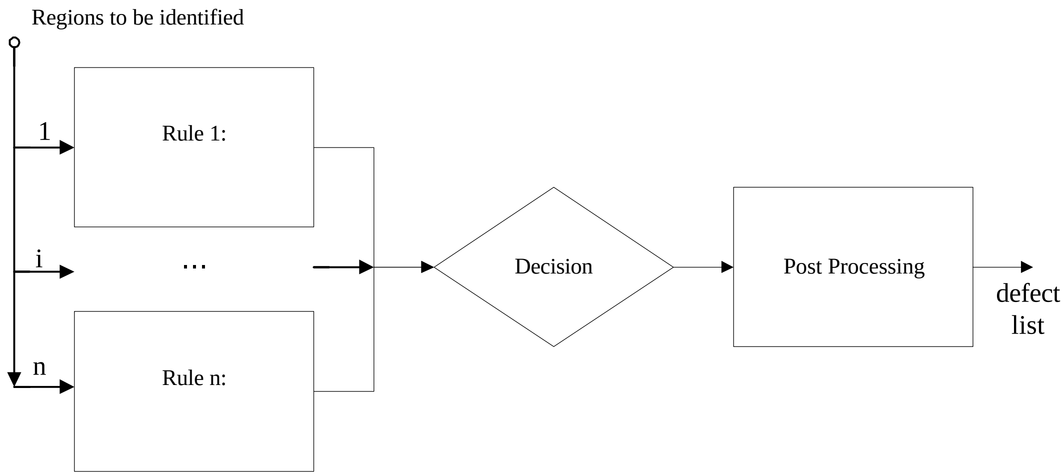

Figure 3. *High-level processing operations are employed as a sequence of rules applied to each candidate defect region identified in previous processing operations.*

Rules applied in this system have the following form:

If a region is
    denser than clear wood, and
    average gray level is darker than clear wood, and
    redder than clear wood, and
    round.
Then
    the region is a knot with confidence value C_t of 0.95.
Else
    the region is a knot with confidence value C_t of 0.05.

The above measures such as "denser", "darker", and "redder" are the basis for an inexact descriptive vocabulary that was used to classify features. Since these measures are not crisp concepts, fuzzy logic is used in making rule evaluations. Fuzzy membership functions used to define memberships in the fuzzy sets are of the form shown in Figure 4. The example shown in Figure 4 is a fuzzy membership function for the set defined by the fuzzy concept "denser than clear wood" for knots. Regions having gray-levels that are significantly less attenuated (darker) than clear wood (e.g. 45 to 95 percent) would have high membership function values. This membership function is derived from frequency histograms of knot/clearwood samples for a particular wood species.

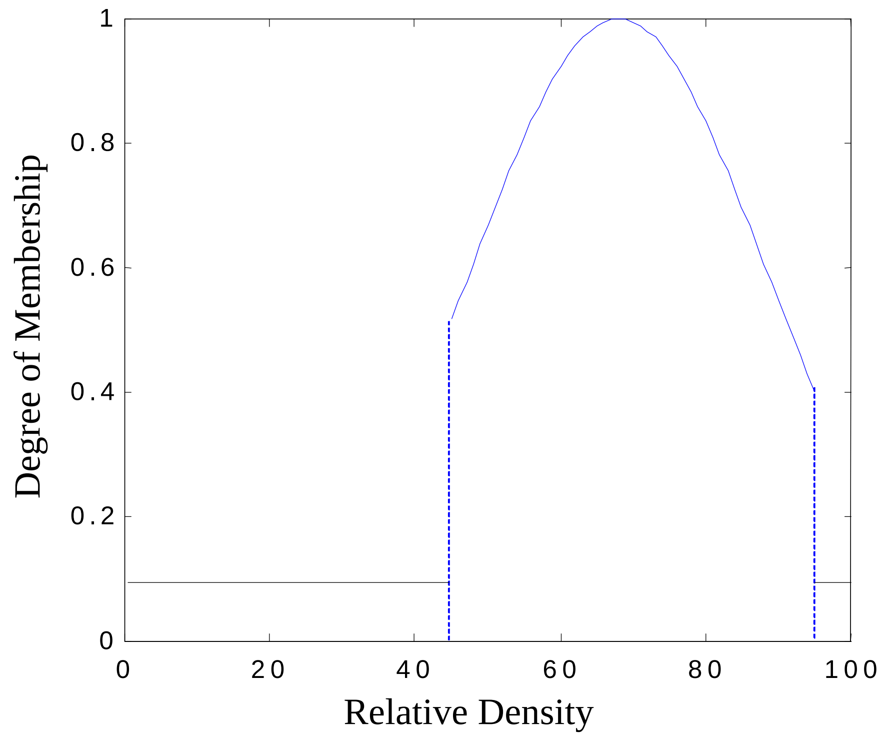

Figure 4. *The degree of membership function used to describe "denser". The percent relative densities associated with red oak knots ranged from 45 to 95 percent more dense than clear wood.*

<u>System Training</u>

Parameters in this machine vision system were developed based on a limited set (less then 150 lumber specimens) of dry surfaced red oak lumber. The system was trained to recognize the following defects in red oak lumber: wane, thin board regions, knot, hole, split, mineral streak, decay, pin knots, worm holes, and stain. Details of the software system development and training can be found in Xiao (2000).

Materials and Methods

Material Selection

Eighty-nine (89) 4/4 red-oak lumber specimens were collected from various mills in the Appalachian region. These boards were different than the sample used to develop and train the system. The lumber was kiln-dried to within 5 to 8 percent moisture content. All boards were at least 10 feet long and 5 to 7.5 inches wide. The boards were re-surfaced with an abrasive planer to remove any surface roughness, stain, or soil and to create a uniform thickness prior to grading evaluation. National Hardwood Lumber Association (NHLA) grades FAS, FAS 1-Face (F1F), #1 Common, #2 Common, and #3A Common were used for the study. The specimen grade mix consisted of 12 FAS boards, 8 F1F boards, 23 #1 Common boards, 20 #2 boards, and 26 #3 Common boards for a total of 89 boards as graded by mill line graders.

Methods

In testing the accuracy of the multiple-sensor defect detection system, the following hardwood lumber grade evaluations were conducted. Comparisons were made between each of these grade evaluations to develop conclusions about the performance of the automated hardwood lumber grading system and where the system could be improved.

1. *Automated Grade* - the board sample was run through the lumber scanning system to generate laser, x-ray, and color images for each board face. These images were saved for subsequent processing and analysis. Subsequent processing utilized current image processing software developed for Virginia Tech's lumber scanning system to automatically generate a "digital map" of lumber grading defects in a standard format that can be used by grading software. Hardwood lumber grading software, UGRS (Ultimate Grading and Remanufacturing System), was used to grade each board based on the generated digital map (Moody et al. 1998).
2. *Digitized Grade* - The boards were manually digitized for all grading defects. Digitization was done by hand and consists of mapping out and classifying all of the defects on the board according to the technique prescribed by Anderson et al. (1993). UGRS was used to establish the true grade of the lumber based on the defects identified during manual digitization. *Digitized* grades are considered to be "ground truth" for evaluating the accuracy of *Automated* grading.
3. *NHLA Grade* - the boards were graded by a NHLA employed certified professional grader.
4. *Line Grade* - the original grade of the boards as graded by the line graders at the various mills from which the board sample was collected.

Results

Grade Distrubution

Figure 5 shows the grade distribution for each of the grade evaluation methods studied. As expected, there is close agreement between the grade distributions for the *NHLA* and *Digitized* grade methods. Note that the *Digitized* grades show less #1 Common grades than the *NHLA* grades. This discrepancy is partly due to extra sensitivity of picking up more defects and slight lumber sidebend or crook in the digitization process. During digitization, there is much more time to consider every possible feature and can result in a slight bias that is more critical of the board's appearance when compared to the NHLA inspector. Precise and consistent definition of what constitutes a true grading defect will be key to developing an effective automated lumber grading system. Future efforts will be needed to develop such definitions that can be readily translated into computer code.

The *Line* grade tends to place more boards in the higher grades compared to the *NHLA* or *Digitized* grade methods (see Figure 5). Also note that the *Line* grader does not grade any boards as #3B Common, a very low value grade. In contrast, the *Automated* grade method tends to place more boards in lower grades. It was observed that some of the Face and better boards were downgraded to #1 Common and some #1 Common boards were downgraded to #2. This observation is illustrated in Figure 5 where the *Automated* grading method resulted in the highest frequency of #2 Common boards. A primary cause of this *Automated* grader discrepancy includes falsely detecting defects in the higher-grade lumber. This false defect detection error and implications will be discussed in more detail later.

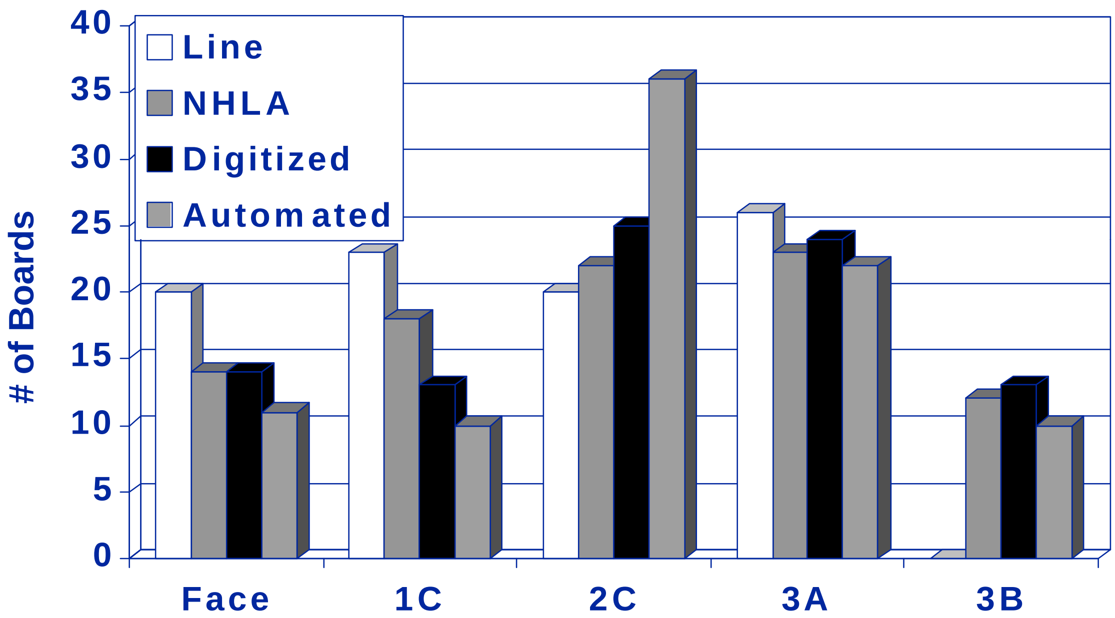

Figure 5. *Lumber grade distribution for each of the grade evaluation methods.*

Board-by-Board Accuracy

Figure 6 shows the board-by-board grading accuracy of the *Automated* lumber grading system compared to the actual or *Digitized* grade. The *Automated* grader correctly grades 56 boards, or 63 percent of the 89 board specimens studied. While this grading accuracy may appear low, it compares favorably with the *Line* grader which correctly grades only 43 boards, or 48 percent of the specimens (see Figure 7). Note that this board-by-board comparison is much stricter than the board distribution comparison shown in Figure 5 because some incorrectly downgraded boards are balanced with incorrectly upgraded boards. The reasons for such board-by-board accuracy results will be discussed in the next section.

		Automated Grader					
		Face or Better	1	2	3A	3B or Below	
	Face or Better	9	3	2			14
Digitized	1	1	5	7			13
	2	1	1	19	3	1	25
	3A		1	7	15	1	24
	3B or Below			1	4	8	13
		11	10	36	22	10	89

Figure 6. *Confusion matrix of board-by-board grading accuracy for the Automated lumber grading system. The most critical classification error can be seen in the #2 Common grade. The automated grader erroneously downgrades 9 boards as #2, where 7 should have been graded #1 and 2 should have been graded 1-Face and better.*

		Line Grade					
		Face or Better	1	2	3A	3B or Below	
Digitized	Face or Better	12	2				14
	1	5	7	1			13
	2	2	10	11	2		25
	3A	1	4	6	13		24
	3B or Below			2	11	0	13
		20	23	20	26	0	89

Figure 7. *Confusion matrix for the Line grader. The most critical classification error can be seen in the #3B or Below grade. The line grader erroneously upgrades 11 boards as #3A and 2 as #2.*

Lumber Value

Table 1 shows the value of the 89-board sample based on each of the grade evaluation methods. These values are based on the May 9 Hardwood Market Report (2000). The *Line* grade results in the highest value of $310 for the sample. This value is 20 % higher than that estimated by the *NHLA* grade. In terms of lumber value, the *Automated* grade is closer to the *NHLA* grade than the *Line* grade. While the values between the *NHLA* and *Automated* grade methods were within 6% from each other, this difference is greater than the 4 % money value allowance that is required by the NHLA grading specification. Even the difference between the *NHLA* and *Digitized* grade methods is slightly greater than this 4% allowance at 4.6%.

Table 1. *Value of the 89 boards for each of the grade evaluation method (May 9, 2000 Hardwood Market Report).*

Evaluation Method	Value
Line Grade	$310
NHLA Grade	$259
Digitized Grade	$247
Automated Grade	$244

Factors that Limit Automatic Grading Accuracy

Defining the "ground truth" or true grade of a board is still a subjective process. For example, in this study 8 of the *NHLA* graded boards were later assigned a different grade by the NHLA inspector. More accurate consideration of board sidebend (crook) in cutting unit calculations was the primary reason why these 8 boards were reassigned a different grade. *Automated* grading can significantly increase grading consistency through more precise measurements and calculations. Since the *Automated* grading method uses UGRS which employs a strict and literal interpretation of the NHLA grading rules, it is suggested that an evaluation procedure similar to the *Digitized* grading method would be the least biased method of evaluation. Nevertheless, establishing a completely unbiased "ground truth" for accurate grading system testing and feedback is difficult. Regardless of any inherent bias found in this study, the following factors contributed significantly to grading discrepancies and will require more careful and precise definition for future R&D that will ensure commercially viable lumber grading technology.

Sidebend

Board sidebend or crook can have a significant impact on the calculation of available cutting units. If sidebend, even a small amount, is ignored the calculation of available cutting units has the tendency to increase. Since an automated system can make precise geometrical calculations, it will tend to downgrade such boards when compared to human graders.

Surface Measure

Differences in the surface measure can cause a grade difference if the measurements for the surface measure calculations are off by even a small amount. For example, the surface measure can be off by 1 unit depending on how precise a human grader measures the width of the board. Therefore, a larger or smaller surface measure estimate could possibly downgrade or upgrade a board, respectively. This raises the question as to why there is a discrepancy in the surface measures. The boards may be close to the borderline between two surface measures and a fraction of an inch or rounding may move the board to one surface measure or another. Since an automated system can make precise length and width measurements, it would easily be able to handle an area measurement system with much higher resolution than the existing manual system.

Cutting Units

In many cases, the available cutting units in a board may be close to the borderline between two grades. For example, if 65 percent of the board's surface measure is available for clear cutting units, it would be graded as a #2 common. But it would be very close to a #1 Common, which requires 67 % of the board's surface measure. Making a critical grading feature smaller or larger (say one quarter of an inch) can mean the difference between two grades. Since an automated grading system can make precise cutting unit measurements and calculations, it would be easy to report available cutting units along with board grade. Knowing the percent of the board that is available for cutting would be valuable information when designating the optimum use of a particular board.

Small Defects, stain and mineral streak

Small defects such as pin knots and worm holes, stain and mineral streak are sometimes difficult to detect at production speeds or it may be subjective as to when these feature types are considered a grading defect. These defects are oftentimes detected by an automated grading system and included in the defect map as a critical defect. In this study, stain or mineral streak was not included as a grading defect in the UGRS graded boards. However, the most significant error observed in the *Automated* lumber grading system was misclassification of certain stain and mineral features as critical knot defects. This error is illustrated in Figure 8 where a burn mark in the wood is falsely detected as a set of knots. Since the training of the system was not trained to classify burn marks (or other innocuous surface discolorations), this finding was not unexpected. Proper training of the system will require not only examples of all possible grading defects, but also examples of other all the possible wood features that are not considered a grading defect.

Figure 8. *Surface marks misclassified as critical grading defects.*

Grading Rough-Green Hardwood Lumber

Figure 8 illustrates how innocuous surface marks on dry surfaced lumber can sometimes be confused with lumber grading defects. Such misclassification errors will be an even greater problem for rough-green lumber where surface conditions can vary widely. Figure 9 illustrates this potential problem by showing a typical image of a red oak board collected at the green chain. The board contains black sawmarks and a portion of the board surface has begun to dry creating a lighter appearance. These conditions pose a significant challenge for automated lumber grading systems. Further R&D will be needed to find the most appropriate scanning technology and develop the computer software that can see through such highly variable "noise" that can be present in wood.

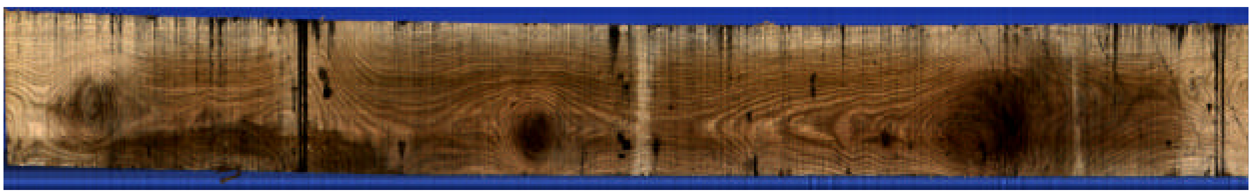

Figure 9. *Surface marks present in rough-green red oak lumber.*

Conclusion

Machine lumber grading systems will be making their debut in the next several years. The primary cost savings from such a system will be realized by producing a more uniform and consistently graded product and by producing a higher value product through optimum lumber remanufacturing. Technology is now available to create such systems. However, adapting this technology for lumber grading applications will take several years. Successfully delivering such grading systems to the end user will depend upon a good understanding by equipment manufacturers, mill managers, and operators alike on the level of sophistication of technology and the associated learning curve that is needed to handle an extremely variable material called “wood”. Virginia Tech is involved in several R&D and education efforts to help apply such new technologies to the forest products industry.

Using a multiple sensor lumber scanning system developed at Virginia Tech, a preliminary automated lumber grading study was conducted on an 89-board sample of dry surfaced red oak lumber. On both a board-by-board and lumber value basis, the automated lumber grader was found to be more accurate and consistent than line graders. Most automated lumber grading discrepancies resulted from board geometry issues (board crook, surface measure rounding, calculation of cutting units, etc.). As far as the lumber scanning technology is concerned, defect recognition improvements should focus on better methods to differentiate surface discoloration from critical grading defects.

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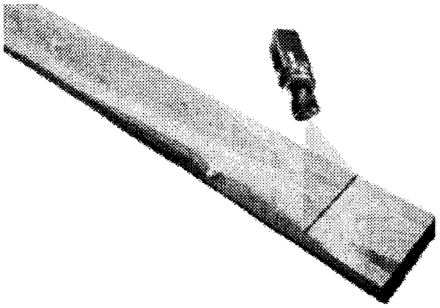

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