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# Automated hardwood lumber grading utilizing a multiple sensor machine vision technology

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## Abstract

Over the last 10 years, scientists at the Thomas M. Brooks Forest Products Center, the Bradley Department of Electrical and Computer 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. Eighty-nine red oak boards were scanned and graded using Virginia Tech's multiple sensor scanning system. The same boards were also manually graded on a normal production line. Precise board grade was determined by manually digitizing the boards for actual board defects. A certified National Hardwood Lumber Association (NHLA) employed lumber inspector then graded the lumber to establish a certified market value of the lumber. The lumber grading system was found to be 63% 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% more accurate than the line graders, which were found to be 48% accurate. Further, the automated lumber grading system estimated lumber value to within less than 6% of the NHLA certified value, whereas the line grader overestimated the lumber value by close to 20%. 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

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future scanning hardware and image processing software to more accurately identify lumber grading features.

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## 1. Introduction

Hardwood lumber is the primary material from which many high-value furnishings are made, including finished floors, cabinets, furniture, millwork, and other household products. Traditionally, the higher grades of preferred timber species (e.g. oak, cherry, walnut, and yellow poplar) have been used by the wood products industry. Consequently, woodworking equipment and the skills of the workforce in this industry have been designed to process wood raw materials that were relatively free from defects, easy to process, and inexpensive to waste. Recent price increases along with a diminishing supply of high quality timber resources have resulted in the production and utilization of lower grade material. The traditional processing technology of this industry is not best suited to efficiently grade and process such materials. Therefore, the wood products manufacturing industry must aggressively explore innovative processes if they are to survive in an increasingly complex and competitive environment.

The development of new processing technologies will require a sensing system that can automatically inspect wood and accurately pinpoint critical features that affect the quality of the final product. Many different sensing methods have been applied to inspection of wood (Szymani and McDonald, 1981; Portala and Ciccotelli, 1992; Ferrar, 1996) including optical, ultrasonic, microwave, nuclear magnetic resonance, and X-ray sensing. These sensing methods have produced positive results in recent years. More recently, research has shown that multiple sensor scanning techniques provide a less ambiguous way to detect many of the features that affect the quality of wood such as knots, decay, mineral streaks, and internal splits (Conners et al., 1997; Bond et al., 1998). This research has been promising because relatively inexpensive sensing and computer technologies are now available.

One highly sought after application of this technology is automated lumber grading. These automated 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 output 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 hardwood lumber grading, 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, 1998) to demonstrate and test applicable scanning technologies. This R&D effort has led to a patented defect detection system for lumber (Conners et al., 1999). The objective of this study is to test the accuracy of this defect detection system on hardwood lumber grading. We will evaluate and discuss critical machine vision issues that must be further addressed before this technology can be used as a commercially viable application to automatic hardwood lumber grading.

## 2. Methods and materials

### 2.1. Scanning methods

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 Fig. 1). To meet the needs of multiple sensor data acquisition and real-time image processing, special purpose hardware was also developed and incorporated into the prototype (Conners et al., 1992; Drayer, 1997; King, 1998; LaCasse, 2001). Scanning generates combined images with a cross board resolution of 1.2 pixels/mm (30 pixels/in.) and a down board resolution of 0.63 pixels/mm (16 pixels/in.) at a linear conveyor speed of 0.6 m/s (2 ft/s). The greater cross board resolution was found to aid in split detection, an important lumber grading feature that requires greater resolution only in the cross board direction. The color, range, and X-ray images were all calibrated to have identical spatial resolution so that a pixel location on any image is referenced to exactly the same location on a lumber specimen.

#### 2.1.1. Color scanning

Color images were collected using a Pulnix TL-2600 RGB line scan camera with a resolution of 864 pixels. The camera was mounted perpendicular to the wood surface, and four linear Fostec fiber-optic light lines were used to illuminate the surface of the lumber with a DC-regulated tungsten-halogen light source (Fostec Type EKE). The Pulnix camera was fitted with two color-balancing filters (Schott numbers FG-6 and BG-34). The camera light balance was calibrated using a Spectralon 75% reflectance target. The three 8-bit color channels were individually shade corrected with a linear function.

#### 2.1.2. Laser range scanning

The laser-based ranging system uses a 30 mW helium–neon gas laser with a 632.8 nm wavelength. A 24-facet polygon scan mirror, rotating at approximately 30 000 rpm, sweeps a point of laser light across the wood surface. The laser line image is captured by two EG&G 128 × 128 pixel array cameras at the rate of 384 frames per s. Special-purpose hardware locates the displacement of the laser line in the collected images and generates 7-bit range data. Through this process, the laser-based range

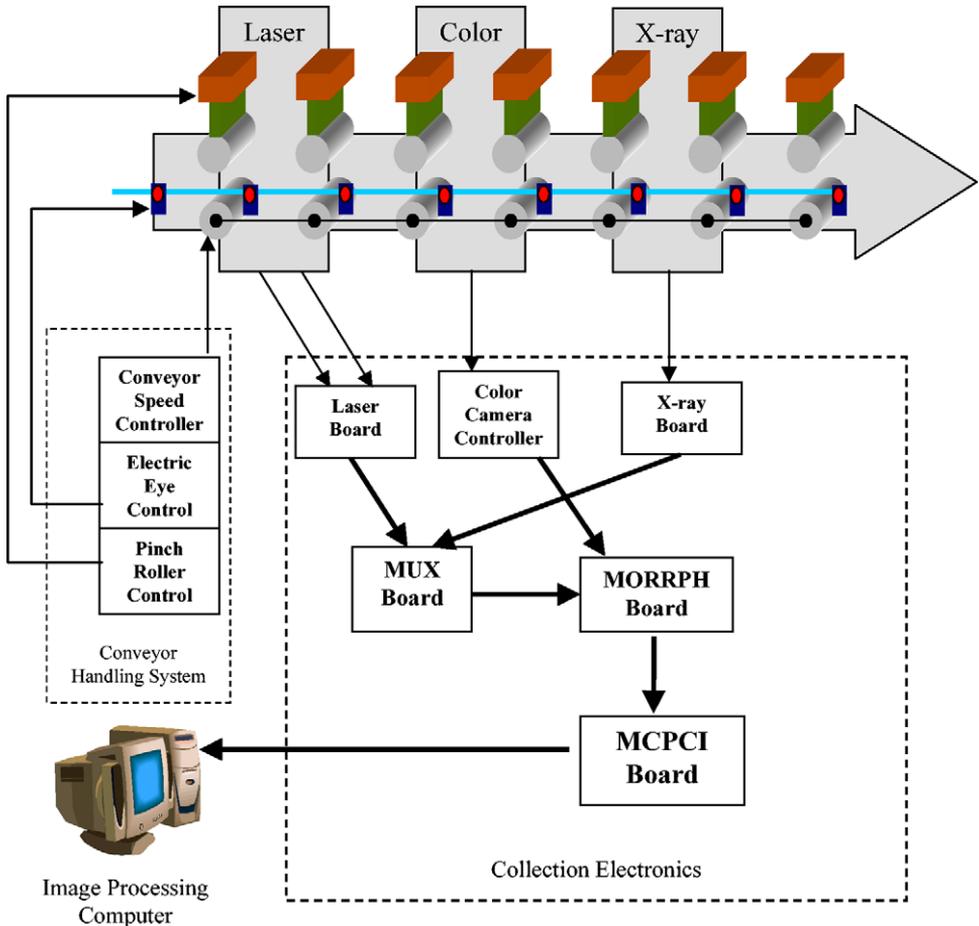


Fig. 1. The multiple sensor lumber scanning system hardware allows for the collection of six channels of registered image data: (1) range, (2) red, (3) green, (4) blue, (5) black and white, and (6) X-ray. Each of these channels of image data is processed in real-time using special purpose image processing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

scanner can measure board thickness variations in the wood surface to within 0.4 mm (1/64 in.).

2.1.3. X-ray scanning

The X-ray system employed an EG&G Astrophysics X-ray source with the radiation energy set to 100 keV and 0.6 mA. The X-ray sensor was a 256-pixel line array manufactured by FISCAN and generates 8-bit X-ray images. The X-ray images are shade corrected using a linear function. The X-ray image contrast was optimized by calibrating the minimum level (highest absorption) with a uniform density (0.94 g/cm<sup>3</sup>) target of 45-mm thick polyethylene.

#### 2.1.4. Image acquisition

Real-time processing hardware was developed at Virginia Tech (Drayer, 1997) to simultaneously collect image data from each scanner with the same spatial resolution (see Fig. 1). Five channels of image data are generated by the three scanners: (1) range, (2) red, (3) green, (4) blue, and (5) X-ray. The collection of image data from each scanner is synchronized using the same clock and then input into the processing hardware. To minimize the computational requirements of the image-processing computer, the processing hardware performs various real-time processing operations such as image shade correction and filtering. The processing hardware also creates a sixth channel of image intensity (black and white) data by averaging the red, green, and blue color channels. The final operation of the processing hardware is the transfer of six channels of spatially registered image data to memory of the image-processing computer. The approximate bandwidth of this image acquisition hardware is 2 Mb/s.

#### 2.2. Image processing methods

The prototype machine vision system developed in this research is responsible for processing the six channels of image data 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 employ fuzzy logic to determine the defect class to which the various regions belong. The machine vision software architecture consists of three major processing modules: (1)

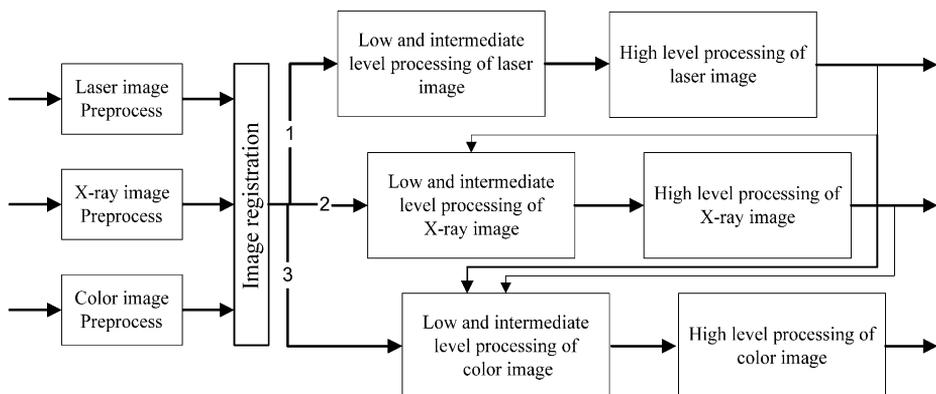


Fig. 2. Preprocessing, low-level, intermediate-level and high-level operations are applied to the image data. The output of the laser-range image operations result in lumber geometry related defect classifications. The output of the X-ray image operations result in density related defect classifications.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

laser image analyzing module, (2) X-ray image processing module, and (3) color image analyzing module (see Fig. 2).

### 2.2.1. Preprocessing

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: background extraction, histogram extraction, and image registration. Background extraction is used to detect the lumber edge in each of the three images. Histogram extraction generates 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.

### 2.2.2. 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 operations are performed on all images to segment clear wood from possible defect regions. For example, Fig. 3 shows a typical histogram of an X-ray image with 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 are used to find the threshold levels to separate pixels representing areas of clear wood with normal density from pixels that might be in defect areas. Similar thresholding techniques are used for each

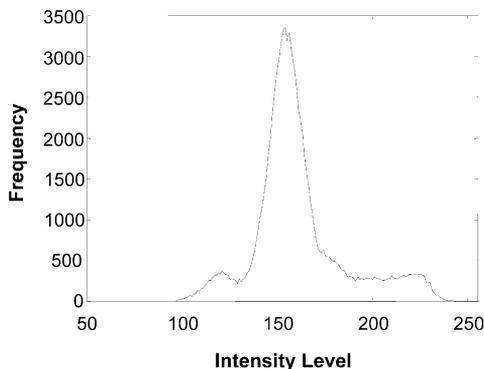


Fig. 3. An X-ray image intensity histogram. Inflection points between peaks are used to select multiple threshold levels for the image.

image modality. The average color intensity image is used for segmenting defect areas rather than each of the red, green, and blue channels separately.

A connected component labeling operation is applied to the thresholded image to form regions that contain possible defects. A four—neighbor connected component region—labeling algorithm was developed in this system to extract regions from the multiple thresholded image (Xiao, 2003). 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. regions containing only 1 or 2 pixels) 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 spatially registered channels of image information provide a rich source of data to extract useful region properties. Region properties are the basis for classifying the various regions a particular grading defect during high-level processing operations. Table 1 lists the region properties measured from each channel of image information for each region identified during low level processing.

### 2.2.3. High-level processing

High-level processing operations are responsible for identifying which defect class is assigned to candidate regions found in low- and intermediate-level processing (see Fig. 4). A number of lumber defect identification rules have been developed in this system. Each of these rules was designed to identify a particular defect class using a fuzzy logic approach (Connors et al., 1999; Xiao, 2003). A rule is applied on every suspect region and 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 merges overlapping defects and filters defect information based on user preferences (e.g. specify minimum allowable defect sizes for a particular grading defect class).

In general, 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 high confidence (e.g. CF = 0.95).
Else
    the region is a knot with low confidence (e.g. CF = 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

Table 1  
Region properties used for defect classification

Property	Description	1	2	3	4	5	6
Intensity	Normalized average region pixel intensity compared with normal (clear) wood	X	X	X	X		X
Height	Height of region	X				X	X
Width	Width of region	X				X	X
Perimeter	Number of pixels on the region boundary	X				X	X
Area	Number of pixels in the region area	X				X	X
Edge	Number of region pixels touching a board edge	X				X	X
Center of mass	Geometric mass center of region	X				X	X
Compactness	Measure of the compactness of a region	X				X	X
Elongatedness	Measure of the elongatedness of a region					X	X

X indicates which images are used to measure a particular feature for regions identified during low-level image processing (1, range; 2, red; 3, green; 4, blue; 5, average color intensity; and 6, X-ray).

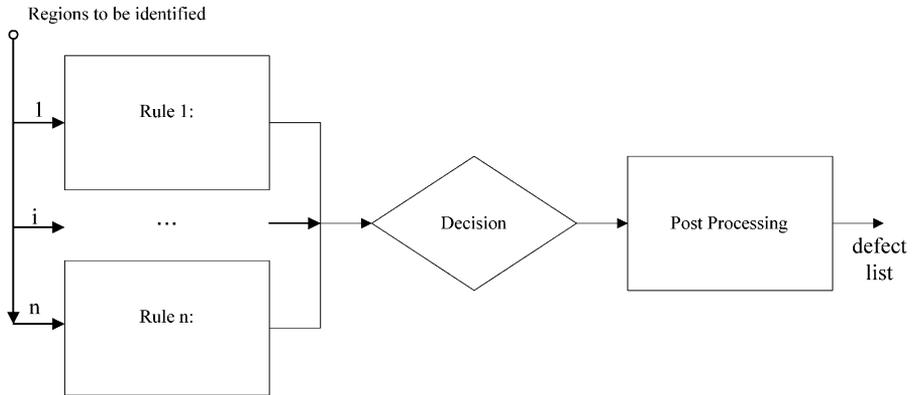


Fig. 4. High-level processing operations are employed as a sequence of rules applied to each candidate defect region identified in previous processing operations.

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 Fig. 5. The example shown in Fig. 5 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 more attenuated (darker) than clear wood (e.g. 45–95%) would have high membership function values. This example membership function was derived from frequency histograms of knot/clearwood training samples for a particular wood species, in this case red oak. Any relative density higher than 95% or lower than 45% would likely be associated with another defect class, which have their own membership functions. This fuzzy logic approach was found to be particularly useful in describing and managing the many overlapping membership functions for different defect classes found in lumber.

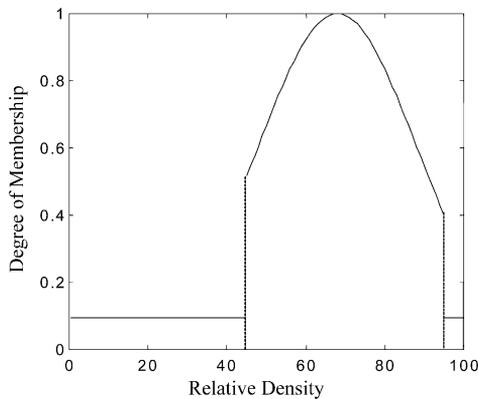


Fig. 5. The degree of membership function used to describe “denser”. The percent relative densities associated with red oak knots ranged from 45 to 95% more dense than clear wood. Membership functions are approximated using an exponential function.

#### 2.2.4. System training

Parameters in this machine vision system were developed based on a limited set (300 lumber samples) of dry surfaced red oak lumber. The system was trained to recognize clear wood and the following defects in red oak lumber: (1) wane, (2) thin board regions, (3) knot, (4) hole, (5) split, (6) mineral streak, (7) decay, (8) pin knots, (9) worm holes, and (10) stain. This developmental sample of lumber was randomly selected to provide at least 40 clear examples of each defect type to train the system. The examples were selected by personnel from a cooperating forest products company to be representative of the grading defects typically encountered in their manufacturing process. Range, color, and X-ray images were collected for each of these examples from which property measurements were made to train the system.

Training the system involved deriving membership functions (e.g. see Fig. 5) that describe the observed variability of region features for each defect type. Frequency histograms of observed region features (Table 1) were generated from defect examples in the training set. Using the frequency histograms, membership functions belonging to each of the ten defect types were constructed for each region property and associated image indicated in Table 1. Further details of the software system development and training can be found in Connors et al. (1999) and Xiao (2003).

#### 2.3. 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 5–8% moisture content. All boards were at least 2.1 m long and between 12 and 19 cm 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, 1998) grades FAS, FAS 1-Face (F1F), #1 Common (1C), #2 Common (2C), and #3A Common (3A) 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.

#### 2.4. Evaluation 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*—each 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 the processing software described earlier 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, Ultimate Grading and Remanufacturing System (UGRS), 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 consisted of mapping out and classifying all of the defects on the board according to the technique described 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 to establish the market grade and value of the lumber.
- 4) *Line grade*—the original grades of the boards, as graded by the line graders at the various mills from which each board sample was collected.

### 3. Results and discussion

#### 3.1. Grade distribution

Fig. 6 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 grade and digitized grade methods. Note that the digitized grade shows fewer #1 Common grades than the NHLA grade. This discrepancy is partly due to extra sensitivity of picking up more defects and slight lumber sidebend or crook in the

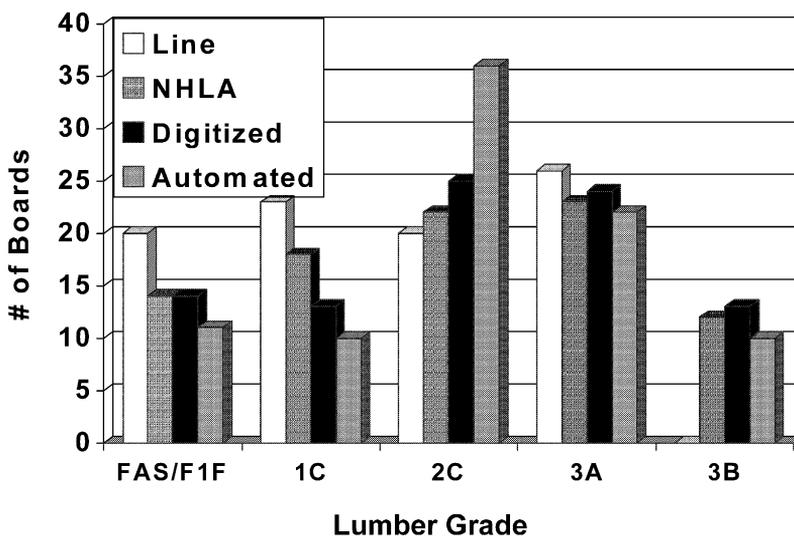


Fig. 6. Lumber grade distribution for each of the grade evaluation methods.

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 with 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 with the NHLA grade or digitized grade methods (see Fig. 5). Also note that the line grade does not grade any boards as #3B Common (3B), 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 Fig. 5 where the automated grade method resulted in the highest frequency of #2 Common boards. A primary cause of this automated grade discrepancy includes falsely detecting defects in the higher-grade lumber. This false defect detection error and implications will be discussed in more detail later.

3.2. Board-by-board accuracy

Fig. 7 shows the board-by-board grading accuracy of the Automated lumber grading system compared with the actual or digitized grade. The automated grade correctly grades 56 boards, or 63% of the 89 board specimens studied. While this grading accuracy may appear low, it compares favorably with the line grade, which correctly grades only 43 boards, or 48% of the specimens (see Fig. 8). Note that this board-by-board comparison is much stricter than the board distribution comparison shown in Fig. 6 where 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.

3.3. Factors that limit automatic grading accuracy

Defining the “ground truth” or true grade of a board is a subjective process. For example, verification procedures in this study found eight of the NHLA grade

		Automated Grader				Totals	
		FAS/F1F	1	2	3A		3B or Below
Digitized	FAS/F1F	9	3	2		14	
	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
Totals:		11	10	36	22	10	89

Fig. 7. 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 nine boards as #2, where seven should have been graded #1 and 2 should have been graded 1-face and better.

		Line Grade					Totals
		FAS/F1F	1	2	3A	3B or Below	
Digitized	FAS/F1F	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
Totals:		20	23	20	26	0	89

Fig. 8. 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.

boards later reassigned a different grade by the same NHLA inspector. More accurate consideration of board sidebend (crook) in grading calculations was the primary reason why these eight boards were reassigned a different grade. Because of such a discrepancy even with a certified grade, the method of using the digitized grade for establishing “ground truth” was established. Furthermore, the automated grading method uses UGRS, which employs a strict and literal interpretation of the NHLA grading rules. As such, 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 due to the subjective nature of identifying lumber defects, the following factors contributed significantly to grading discrepancies and will require more careful and precise definition for future research and development that will ensure a commercially viable lumber grading technology.

### 3.3.1. Sidebend

Board sidebend or crook is the tendency of the board to bow in the side-to-side direction. Any deviation in a board from a perfect straight line can have significant impact on cutting yield. As such, board sidebend has an impact on the calculation of the available clearwood cutting units used to assign board grade. Higher grades are assigned to boards with higher cutting units relative to the total board surface area. If sidebend 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 with human graders.

### 3.3.2. Surface measure

Surface measure is the total board surface area in square feet ( $0.093 \text{ m}^2$ ) and is calculated by multiplying board length by board width. Surface measure is rounded to the nearest whole number. 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 (i.e.  $1 \text{ ft}^2$ ) 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 (i.e.  $1/2 \text{ ft}^2$ ), and a small misjudgment 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.

### 3.3.3. Percentage of clear cutting units

In many cases, the percentage of available cutting units in a board relative to its surface measure may be close to the borderline between two grades. For example, if 65% 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 in such borderline cases. 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.

### 3.3.4. 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 Fig. 9 where a planer burn mark in the wood is falsely detected as a set of knots. Since 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.



Fig. 9. Surface marks misclassified as critical grading defects.

Table 2

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 certified grade	259
Digitized grade	247
Automated grade	244

### 3.4. Lumber value

Table 2 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 certified grade. The NHLA certified grade is commonly used to settle disputes in lumber grading. 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%. The main conclusion that can be drawn from these results is that precise definition of what constitutes a grading defect in lumber is needed before the true accuracy of automated lumber grading can be scientifically assessed.

### 3.5. Grading rough-green hardwood lumber

Fig. 9 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. Fig. 10 illustrates this potential problem by showing a typical image of a red oak board collected at a location in the hardwood lumber manufacturing process where boards are typically graded. The board at this point in time 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



Fig. 10. Surface marks present in rough-green red oak lumber.

technology and develop the computer software that can see through such highly variable “noise” that can be present in wood.

#### **4. Conclusion**

The development of machine lumber grading is a technology that can add significant value to the products being produced by the hardwood lumber manufacturing industry. 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”.

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. A lumber digitization procedure was developed to establish lumber grade “ground truth”. 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. Accurate differentiation will be critical to the success of machine grading systems in an actual manufacturing environment where many innocuous surface discolorations can arise from material handling or from the natural variation in wood. Concerning the definition of grading standards, future work in new machine lumber grading standards will need to be developed that precisely defines what lumber features are to be considered a “grading defect”.

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