Identifying and Locating Surface Defects in Wood: Part of an Automated Lumber Processing System

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Abstract—Continued increases in the cost of materials and labor make it imperative for furniture manufacturers to control costs by improved yield and increased productivity. This paper describes an Automated Lumber Processing System (ALPS) that employs computer tomography, optical scanning technology, the calculation of an optimum cutting strategy, and a computer-driven laser cutting device. While certain major hardware components of ALPS are already commercially available, a major missing element is the automatic inspection system needed to locate and identify surface defects on boards. This paper reports research aimed at developing such an inspection system. The basic strategy is to divide the digital image of a board into a number of disjoint rectangular regions and classify each independently. This simple procedure has the advantage of allowing an obvious parallel processing implementation. The study shows that measures of tonal and pattern related qualities are needed. The tonal measures are the mean, variance, skewness, and kurtosis of the gray levels. The pattern related measures are those based on cooccurrence matrices. In this initial feasibility study, these combined measures yielded an overall 88.3 percent correct classification on the eight defects most commonly found in lumber. To minimize the number of calculations needed to make the required classifications a sequential classifier is proposed.

Index Terms—Automatic inspection system, sequential classifier, texture analysis.

I. INTRODUCTION

WHEN producing parts for furniture and other assembled wood products, logs (mainly hardwoods) are first sawn into different lumber grades with defects randomly located throughout the board. The defective lumber is then remanufactured into smaller parts and the defects removed by ripping and cross cutting. The process is labor intensive, and saw kerf losses alone waste substantial volumes of valuable lumber.

Consider now an automated lumber processing system (ALPS) for producing the same parts. Hardwood logs enter the process stream and are scanned by industrial photon tomography (IPT) to nondestructively locate internal knots and establish log geometry. A series of such tomographs results in a three-dimensional image of knots within the entire log. Using this information, an optimum log breakdown strategy is computed to maximize grade or value yield. The computer-driven breakdown saw would automatically position and turn the log as needed, activate the log dogs and carriage stroke, and set feed speeds. Most boards, however, will still contain visible surface defects (i.e., knots, wane, stain, worm holes, checks), many of which cannot be detected using tomography.

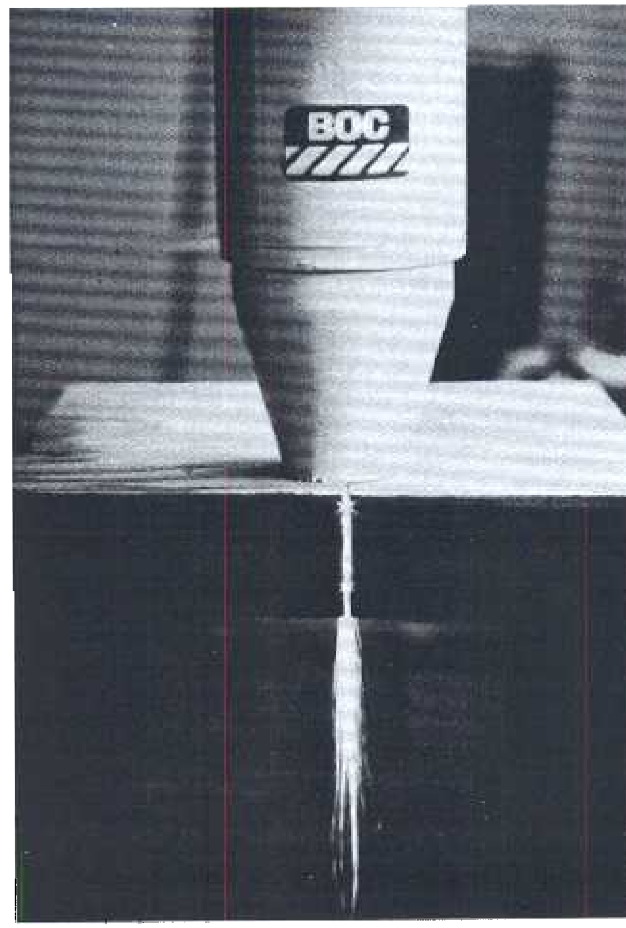

Fig. 1. Photograph of a continuous carbon dioxide laser cutting a 1 in thick board in a direction across the grain. (Photo courtesy of the British Oxygen Company.)

After drying and light surfacing, the boards are scanned on both surfaces using optical imaging devices. The resulting digital images are analyzed by the computer to identify types of surface defects and provide coordinate data on their location. The image-derived defect data are then used to compute an optimum cutting pattern for each board, thus yielding the maximum number of parts for a given cutting bill.

In the envisioned ALPS process, parts are cut from the board using a numerically controlled high-power laser directed by the computer derived optimum cutting pattern (Fig. 1). Advantages of laser cutting are numerous. Most important to this

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process is the small kerf (approximately 0.015 in) and the ability to start and stop cutting at any location.

Lastly, parts are optically scanned for quality and sorted by size. Residue material is chipped and used as fuel.

This paper reports research aimed at one portion of the ALPS process—development of the automated inspection system needed to identify and locate visible surface defects. It was this system whose technical feasibility was most in doubt. The results indicate that both measures of tonal properties as well as pattern properties of wood are required. The tonal measures employed are the mean, variance, skewness, and kurtosis of the gray levels. The pattern related measures are those based on cooccurrence matrices [1]-[3].

The basic strategy employed is to divide the image of the board into a number of disjoint rectangles and classify each rectangle independently. The procedure has the advantage of allowing a straightforward parallel processing implementation. To further accelerate the analysis process a sequential classifier is devised; one which requires the evaluation of the more computationally complex measures only in those instances where absolutely needed.

II. Previous Research on Defect Detection Systems

The desire to optimize sawing decisions has lead many investigators to study potential defect detection systems. The difficulty in creating such systems is the high degree of inherent variability, both among and within a species, of those characteristics which define a defect.

A defect is considered to be any characteristic which makes wood unsuitable for a given use. For purposes of this discussion, lumber defects will be grouped into two classes: 1) biological defects which include natural defects and defects caused by fungi; and 2) manufacturing defects which include defects caused by sawing, seasoning, planing, and material handling practices. A variety of different sensors have been investigated to detect such defects. These include ultrasound, microwave, X-ray, neutron, and optical methods. A summary of the known capabilities of these transducers is given in [4].

Optical imaging devices can seemingly detect more surface defects than any other method and thus appears the best approach in applications where appearance is important, as in furniture parts.

Defect detection systems based on optical scanners can best be categorized by the type of scanner employed—laser scanners and cameras. Two laser scanning systems have been developed for detecting defects. The first is a laser scanner and automatic cut-up system, developed by Bendix Research Laboratories and Bendix Forest Products Co. (now the American Forest Products Co.) [5], [6]. The second is the Plessey optical defect detection apparatus, currently being developed by the Plessey Co., Ltd. in cooperation with Weyerhaeuser Co. [7], [8].

The Bendix system consists of a laser scanner and minicomputer. The scanner is a double-sided laser unit which sequentially illuminates both sides of the board. The laser beam passes through a beam-reducing telescope to provide a spot size approximately 1 mm in diameter. The beam is split and passed onto a rotating mirror prism and several mirrors. The scattered light from the lumber is detected by 4 photomultiplier type assemblies. These signals are processed by high-pass and low-pass analog circuits to accentuate all cracks and larger defects, respectively. The analog signals are quantized and digitally processed before being transmitted to the minicomputer. Because the motion of the board through the scanner is continuous and at constant speed, the line scans on one side of the board are interleaved with the scans on the other side. Scanning rate is 20 lines/in for each side.

The minicomputer software processes and filters the incoming data, calculates the size and location of defects, and determines the optimum crosscut and ripcutting pattern. The computer then commands two automatic saws to remove defects, one fixed and one movable.

The laser scanner can detect splits, checks, and red (tight) and black (loose) knots of varying sizes. The lighter colored flaws and certain types of edge grain, however, have proved difficult to detect [5], [6] and acceptable blemishes are sometimes detected as defects. Therefore, an Upstream Human Inspection (UHI) station is used to compensate for the scanner deficiency by either enhancing light color or indistinct flaws and edge defects with a black felt tipped pen; or suppressing nonflaws, such as handling marks, and acceptable flaws, such as light stain, with a reflective marking paint. However, system performance proved limited by the skill of the UHI to compensate for the idiosyncrasies of the automatic inspection system. The process is no longer in service.

The other laser detection and cut-up system is described in detail in the patents of Matthews and Beech [7], [8]. The system was originally designed for automatic grading of lumber. The apparatus, which is still being developed, is reputedly suitable for detecting defects in rough sawn and surfaced lumber. Detection and limited differentiation of defects such as knots, blue stain, and certain kinds of rot are achieved by a laser scanner and suitable photodetectors and filters. More detailed information is not available at this time.

The Iggesund Opti-Edger is a defect detection system using cameras to scan boards. It is used to determine both board geometry and defects—wane, knots, and other characteristics which may affect quality. The detected variations of board quality are registered in a computer in which grading criteria and prices of all sizes and grades can be entered via a keyboard. The computer operates an automatic control and feed system which performs the edging procedure as determined by the system.

Detection systems designed to date are not capable of detecting small defects important in furniture rough mill operations and other appearance-sensitive applications. Such marginal flaws require manual suppression or enhancement of their detection capability. Also, present systems cannot differentiate between defects except for the partial differentiation offered by the Plessey scanner.

The ALPS system is similar in concept but is meant to be significantly more sophisticated than existing lumber processing systems. Like the current systems, ALPS will automatically inspect boards to detect defects, compute an optimal cutting strategy based on the location of defects, and cut the boards

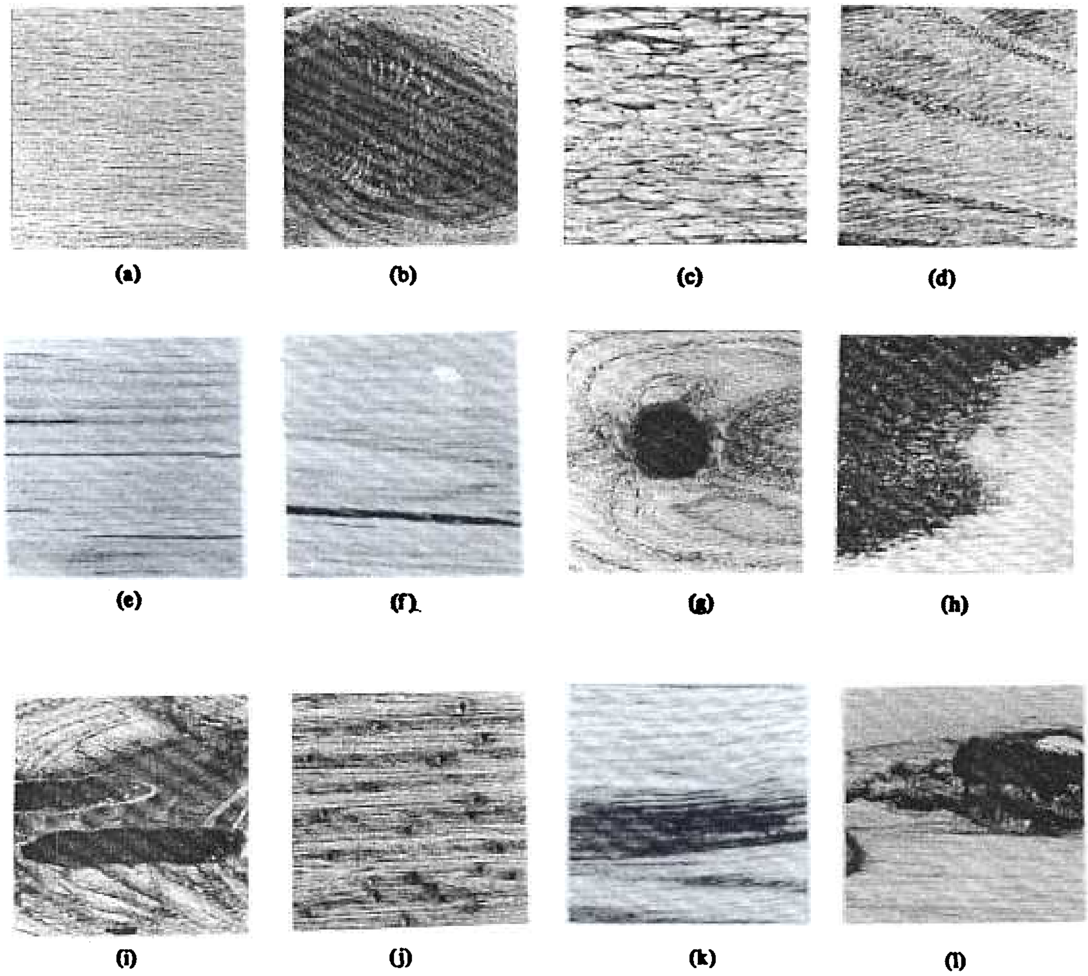


Fig. 2. Clear wood and some important defects visible on the surface of southern red oak. (a) Clear wood. (b) Knot. (c) Incipient decay. (d) Stain. (e) Check. (f) Split. (g) Hole. (h) Wane. (i) Grub hole. (j) Worm hole. (k) Mineral streak. (l) Bark pocket.

into the desired pieces. However, unlike the existing systems, ALPS will not only be able to detect a wide range of surface defects but classify them. Thus, ALPS will provide the capability to selectively choose which defects may appear in each piece of a cutting bill. This differentiation is important because it allows the manufacturer to leave certain defects in parts, such as those which do not reduce marketability or adversely affect the mechanical strength or parts hidden from view.

III. The Image Analysis Problem

A major element in developing ALPS involves solving the image analysis problem. The difficulty is associated with the natural variation in which defects manifest themselves. No two knots are exactly the same size or shape. Even clear wood varies, each piece having a unique wood grain not appearing in any other board. Additionally, the appearance of clear wood and the characteristics of defects vary between wood species.

The computer must be able to perform two tasks. First, it must be able to locate the position and extent of each defect present. Secondly, it must be able to identify the type of defect present at each location. The need for the latter results from the variety of uses for the parts. Some parts may be used as table tops and are always visible. Such parts are usually completely free of defects. Other parts may be used in the frame of a sofa, completely out of sight. A major requirement for such a part is that it be free of defects which would reduce its strength.

Fig. 2 shows some typical patterns of clear wood and defects that must be recognized by the computer. Table I gives a more

TABLE I
A List of Many of the Possible Defects in Wood

Sound Knots (Red Knots)	Checks
Unsound Knots (Dark Knots)	Pitch Pockets
Holes	Pitch
Grub Holes	Pith
Worm Holes	Bark Pockets
Steep Grain	Stain
Spiral Grain	Incipient Decay
Burl	Saw gauge
Torn Grain	Skip Planning
Splits	Planer Burn

extensive list of important defects. Examination of Fig. 2 shows that tonal properties of some defects show substantial differences. For example, knots are significantly darker than clear wood while decay is lighter. Consequently, measures which gauge tonal properties would seem important in the computerized analysis.

However, tonal measures alone do not seem sufficient. Consider, for example, that both checks and splits appear darker than clear wood just as knots do. The difference is that checks and splits are "long and narrow" rather than "round." Hence the pattern they present is also important. As another example, there is an area around each knot which is about the same shade as clear wood but which has a wood grain that is unsuitable for visible furniture parts. This undesirable grain should be removed with the knot; it is part of the "extent" of the knot defect. Again the pattern is important. Therefore, measures which gauge pattern would seem important especially in differentiating the type of defect present at a particular location.

The goal of the image analysis problem is not only to devise a set of measurements which can accurately perform the necessary classifications but also to devise a scheme which requires the minimal number of calculations to obtain the desired classification. Consequently, the decision making logic should be designed so as to minimize the number of calculations required in the examination of each board.

IV. Image Analysis and Pattern Recognition Methods

A straightforward method for attacking this problem is to subdivide an image of a board into a number of disjoint rectangular regions and independently determine whether each region contains only clear wood or a particular type defect. Not only is this method simple, but it lends itself to a parallel processing implementation. Consequently, this approach was adopted in the feasibility study.

A. Measures Gauging Tonal Properties

Tonal property measures computed for each region were as follows:

1) the mean

$$\mu = \sum^{L-1} l P(l); \quad (1)$$

2) the variance

$$\sigma^2 = \sum_{l=0}^{L-1} (l - \mu)^2 P(l); \quad (2)$$

3) the skewness

$$s = \sum_{l=0}^{L-1} (l - \mu)^3 P(l)/\sigma^{3/2} \quad (3)$$

4) the kurtosis

$$k = \sum_{l=0}^{L-1} (l - \mu)^4 P(l)/\sigma^2; \quad (4)$$

where $P(l)$ is the estimated probability of gray level l occurring within a particular region and L is the total number of possible gray levels in the image.

To make these measures meaningful the same lighting conditions were used to scan all the boards. Further, a shading corrector was used to remove any nonuniformities in either camera response or lighting across the scanner's face. Note both controlled lighting conditions and the necessary input to a shading corrector can be obtained by appropriately designing ALPS.

B. Measures Gauging Pattern Qualities

The patterns presented by clear wood or defect are classic example of texture patterns. Consequently, texture measures were employed to gauge these qualities. The measures used were based on cooccurrence matrices [1]-[3]. This particular texture analysis approach was chosen because it has proven useful on a variety of texture analysis problems [9]-[15], comparison studies have shown it to be a superior method [16], [17], and perceptual psychology studies have shown it theoretically capable of matching a level of human perceptual performance [18], [19].

To describe the SGLDM two definitions are required.

Definition 1: A *tile* T is a closed topological disk.

Definition 2: A function $\sigma: E^2 \to E^2$ is called an *isometry* or *congruence* transformation if it maps the Euclidean plane onto itself and if the function preserves distance. That is, if $\vec{x}$ and $\vec{y}$ are points E^2, then $\|\vec{x} - \vec{y}\| = \|\sigma(\vec{x}) - \sigma(\vec{y})\|$.

A cooccurrence matrix $S(\vec{\delta}, T) = [s(i, j, \vec{\delta}, T)]$ is a matrix of estimated second-order probabilities where each element $s(i, j, \delta, T)$ is the estimated probability of going from gray level i to gray level j given the displacement vector $\delta = (\Delta x_1, \Delta x_2)$ and T, the region size and shape used to estimate the probabilities. In this context T is a tile such that $s(i, j, \vec{\delta}, T)$ is estimated from the restriction of the picture function $g(\vec{x})$ to $\sigma(T)$ where σ is a translation isometry. Computationally $S(\delta, T)$ is determined using the equation

$$s(i, j, \delta, T) = \frac{\mathcal{O}\{\vec{x} \mid \vec{x}, \vec{x} + \vec{\delta} \in \sigma(T), g(\vec{x}) = i, g(\vec{x} + \vec{\delta}) = j\}}{N}$$

where $N = \mathcal{O}\{\vec{x} \mid \vec{x}, \vec{x} + \vec{\delta} \in T\}$ where $\mathcal{O}$ denotes the order of the set, i.e., the number of elements.

In what follows it is frequently convenient to consider $\delta = (\Delta x_1, \Delta x_2)$ not in a Cartesian form but rather in a polar form $\vec{\delta} = (d, \theta)$ where $d = \max [\Delta x_1, \Delta x_2]$ and $\theta = \arctan (-\Delta x_2 / \Delta x_1)$. In this polar form d is called the intersample spacing distance and θ is called the angular orientation. (Fig. 3 illustrates these concepts.)

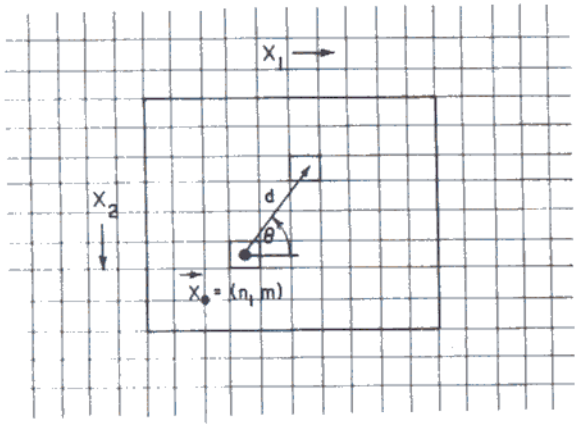
In this study six measures are computed from each matrix $S(\vec{\delta}, T)$. These are as follows:

1) inertia

$$I(\delta, T) = \sum_{i=0}^{\mathcal{L}-1} \sum_{j=0}^{\mathcal{L}-1} (i - j)^2 s(i, j, \vec{\delta}, T); \quad (5)$$

2) cluster shade

$$A(\delta, T) = \sum_{i=0}^{\mathcal{L}-1} \sum_{j=0}^{\mathcal{L}-1} (i + j - \mu_{x_1} - \mu_{x_2})^3 s(i, j, \vec{\delta}, T); \quad (6)$$



DIGITAL IMAGE GRID

Fig. 3. Given that the gray level of the pixel at location $\vec{x}_0 = (n, m)$ is i, the element $s(i, j, \vec{\delta}, T)$ of the matrix $S(\vec{\delta}, T)$, $\delta = (\Delta x_1, \Delta x_2) = (2, -3)$, is the estimated probability that the pixel whose location is $\vec{x}_0 + \vec{\delta}$ will have gray level j. Here the tile T specifies that the region from which $S(\vec{\delta}, T)$ was computed is an 8×8 square. The special polar form of δ is given by $d = 3$, $\theta \simeq 56.3°$.

3) cluster prominence

$$B(\delta, T) = \sum_{i=0}^{\mathcal{L}-1} \sum_{j=0}^{\mathcal{L}-1} (i + j - \mu_{x_1} - \mu_{x_2})^4 \, s(i, j, \vec{\delta}, T); \tag{7}$$

4) local homogeneity

$$L(\delta, T) = \sum_{i=0}^{\mathcal{L}-1} \sum_{j=0}^{\mathcal{L}-1} \frac{1}{1 + (i - j)^2} s(i, j, \vec{\delta}, T); \tag{8}$$

5) energy

$$E(\delta, T) = \sum_{i=0}^{\mathcal{L}-1} \sum_{j=0}^{\mathcal{L}-1} [s(i, j, \vec{\delta}, T)]^2; \tag{9}$$

6) entropy

$$H(\delta, T) = -\sum_{i=0}^{\mathcal{L}-1} \sum_{j=0}^{\mathcal{L}-1} s(i, j, \vec{\delta}, T) \log(s(i, j, \vec{\delta}, T)); \tag{10}$$

where

$$\mu_{x_1} = \sum_{i=0}^{\mathcal{L}-1} i \sum_{j=0}^{\mathcal{L}-1} s(i, j, \vec{\delta}, T)$$

$$\mu_{x_2} = \sum_{i=0}^{\mathcal{L}-1} \sum_{j=0}^{\mathcal{L}-1} j s(i, j, \vec{\delta}, T)$$

and where $\mathcal{L}$ is the number of gray levels in the processed image.

Note that the second-order measures defined in (5)–(10) are functionally related to the values of the first-order measures defined in (1)–(4) [20]. This is most undesirable. One should want an independence among measures gauging tonal qualities from those gauging pattern qualities. Further, for computational purposes the dimensions of the matrices $S(\vec{\delta}, T)$ should be kept as small as possible. This implies that the number of gray levels in the digital image must be reduced after computation of the first-order measures but before computation of the second-order measures. If this reduction is not done properly important picture information can be lost.

Consequently, after the first-order measures are computed an equal probability quantizer (EPQ) algorithm [20] is applied to each rectangular region. The EPQ accomplishes both objectives simultaneously. First it assigns new gray levels to the image in such a way that $P(i) = 1/\mathcal{L}$ for $i = 0, \cdots, \mathcal{L} - 1$ where $\mathcal{L}$ is the number of gray levels in the reduced image. Note $\mathcal{L} < L$, where L is the number of gray levels in the original digital image. Since each image is transformed into one which has a uniform probability distribution the second-order measures are no longer dependent on the original tonal properties. Secondly, it has been shown that the EPQ provides a near optimal way to reduce the number of gray levels so that the reduced image contains all the important information contained in the original image [21]–[26].

C. *Pattern Recognition Methods*

In the study two different pattern recognition procedures are used. One procedure is a pairwise multiclass classification scheme. Using this procedure the process for deciding to which of K possible classes a region belongs is broken up into $\binom{K}{2} = K(K-1)/2$ class-pair decisions. The result of each of these class-pair decisions is tabulated and the region is considered a member of the class into which it was placed the most times. It is assumed that each class-conditional density function is normal and the *a priori* probabilities of the K classes are all equal. Each class-pair decision is made using a Bayes method. The measures used are chosen using a forward sequential search measurement selection algorithm. This algorithm is used to select the "best" measures to make each pairwise decision.

The second classification procedure is used to determine whether a region is entirely clear wood or whether it is not entirely clear wood. Assuming that the density function of measures computed from samples which are entirely clear wood is $f(\vec{x}) = N(\vec{\mu}, \Sigma)$, a standard chi-squared test can be used to make this determination [27]. Using this procedure a region is considered to be clear wood if the measurement vector $\vec{x}$ computed from it is such that

$$(\vec{x} - \vec{\mu})^t \, \Sigma^{-1} (\vec{x} - \vec{\mu}) \leq T. \tag{11}$$

Otherwise the region is considered to contain a defect. This classification strategy will prove useful in formulating the sequential classifier. A forward sequential search algorithm is employed to pick the best measures to use in the chi-squared test and to establish the best value of T to use. This measurement selection procedure attempts to minimize the probability of misclassification.

V. The Feasibility Study

The purpose of the feasibility study was to determine whether the combination of tonal and textural quality measures could:

1) accurately differentiate defects from clear wood,
2) accurately identify the type of defect present.

In performing the study it was decided to consider only surfaced lumber. The species selected for the study was southern red oak.

A database of approximately 500 boards was collected. Each board contained one or more of the defects given in Table I. The data collected represent the variation and relative fre-

Fig. 4. An illustration of the light and dark bark. *A* shows appearance of dark bark. *B* shows appearance of light bark.

quency of occurrence of each defect. Preliminary examination of the boards indicated that only a subset of the types of defects could be considered as too few samples of some defects were included in the database. The classes which could be considered were: 1) clear wood; 2) knots; 3) mineral streak; 4) decay; 5) stain; 6) wane; 7) splits and checks; 8) grub holes and holes; 9) dark bark; and 10) light bark. Splits and checks were combined to form one class since there were not enough samples of each and also since they present very similar visual patterns. Similarly, grub holes and holes were combined. On the other hand, the defect bark pockets were split into two classes, light and dark bark, so that more visually similar pattern groupings could be obtained. Fig. 4 illustrates the difference between light and dark bark.

Boards containing the above defects were scanned to create a digital image of each board. The images were 512 X 512 resolution black and white images containing 256 gray levels. The spatial resolution was about 64 pixels to the inch. A shading correction was performed on each image. This correction was based on the digitized values obtained from a gray colored test pattern. The test pattern was scanned on a regular basis (after every ten scans) to check for any drift in the light sources. The shading correction employed removed any such drift as well as any nonuniformities because of either lighting conditions or because of nonuniformities in response across the face of the camera tube.

Once the boards had been scanned and the shading correction performed a set of training data was selected. Each training sample was a square 64 X 64 pixel region containing one type of defect or clear wood. The region size of 64 X 64 pixels (approximately a square inch) was chosen heuristically. If any defect was present in 64 X 64 region, regardless how small, the region was assigned to that defect class. Fig. 5 illustrates the possible extremes which can occur for two regions containing a knot. In part (a) the knot comprises most of the region while in part (b) the knot occupies only a small percentage of the area.

The first-order measures were extracted from each of the training samples and the EPQ algorithm was applied to the region to reduce the number of gray levels from 256 to 8. The second-order measures were then computed from the reduced "image." Both the first- and second-order measures are put in the measurement vector for that region.

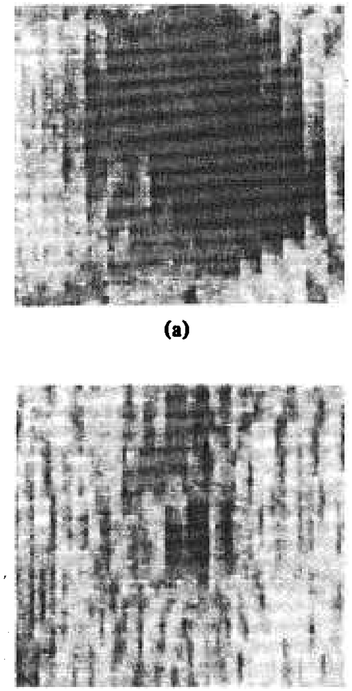


Fig. 5. The extremes which can occur for two regions both assigned to the knot class. Note in (a) the knot comprises most of the region while in (b) the knot occupies a small percentage of the region area.

The choice of eight gray levels in the reduced image was based on examining the EPQ reduced image and the original image. Typically, one wants to have the reduced image contain as few gray levels as possible yet still retain all the important pattern information contained in the original image.

Several $\vec{\delta} = (d, \theta)$ values were used in computing the texture measures. The θ values were 0°, 45°, 90°, 135°. The d values were 1, 2, 4, 8, and 16. In addition, along the $\theta = 0°$ direction a d value of 32 was used.

VI. Results

The classification accuracies obtained are summarized in Tables II-IV. Table II shows the classification results obtained when only the first-order tonal measures defined in (1)-(4) were used. Each row, say row k, of the table shows how examples of class ω_k were classified by the computer. For example, the second row shows that only 30.23 percent of the knots were correctly classified using the first-order measures with 11 of the 86 knot samples being called holes, 9 splits and checks, 19 mineral streaks, etc.

As is easily observed, first-order measures are not sufficient to accurately classify the type of defect present. This is as one would expect. However, if one examines the last row of the table it can be seen that only 16 of the 192 samples of clear wood were incorrectly classified as being a defect, giving a 91.67 percent accuracy. Further, the last column of the table shows that only 13 of the 810 defect samples were incorrectly labeled as clear wood by the computer, giving a 98.40 percent accuracy.

The overall correct classification using only first-order measures was 63.13 percent. All four of the first-order measures were shown to be useful by the measurement selection program.

TABLE II
RESULTS OBTAINED USING ONLY THE FIRST-ORDER TONAL MEASURES DEFINED IN (1)–(4)

VERIFIED CLASSIFICATION \ COMPUTER CLASSIFICATION	DE	KN	WN	ST	HL	SCH	MS	LB	DB	CW	TOTAL	PERCENT CORRECT
DE	91	0	0	2	0	4	1	0	0	2	100	91.00
KN	1	26	7	0	11	9	19	3	10	0	86	30.23
WN	1	2	77	3	5	0	2	9	1	0	100	77.00
ST	1	0	7	67	0	7	0	16	0	1	99	67.68
HL	1	12	2	0	49	3	0	0	14	0	81	60.49
SCH	2	0	1	0	0	73	3	3	13	5	100	73.00
MS	8	6	11	1	1	9	61	1	2	0	100	61.00
LB	1	3	10	18	0	13	4	20	2	5	76	26.32
DB	0	11	1	0	6	11	1	2	36	0	68	52.94
CW	2	0	0	10	0	1	1	2	0	176	192	91.67
TOTAL	108	60	116	101	72	130	92	56	78	189	1002	
OVERALL PERCENTAGE CORRECT CLASSIFICATION												63.13

TONAL MEASURES

TABLE III
RESULTS OBTAINED USING ONLY THE SECOND-ORDER TEXTURE MEASURES DEFINED IN (6)–(10)

VERIFIED CLASSIFICATION \ COMPUTER CLASSIFICATION	DE	KN	WN	ST	HL	SCH	MS	LB	DB	CW	TOTAL	PERCENT CORRECT
DE	90	0	[illegible]	1	0	0	1	[illegible]	[illegible]	[illegible]	100	90.00
KN	3	74	[illegible]	[illegible]	[illegible]	0	6	[illegible]	[illegible]	[illegible]	86	[illegible]
WN	8	4	78	4	[illegible]	0	1	2	0	2	100	78.00
ST	4	0	3	59	0	[illegible]	0	2	0	30	99	59.60
HL	0	14	0	0	60	0	2	0	4	1	81	74.07
SCH	3	1	2	4	2	69	3	2	0	14	100	69.00
MS	2	0	0	0	2	2	93	0	1	0	100	93.00
LB	1	1	7	2	1	1	1	47	4	11	76	61.84
DB	5	4	3	0	13	1	3	1	38	0	68	55.88
CW	1	0	4	4	0	4	1	1	0	177	192	92.19
TOTAL	117	98	101	74	82	78	105	60	49	238	1002	
OVERALL PERCENTAGE CORRECT CLASSIFICATION												75.96

TEXTURE MEASURES

TABLE IV
RESULTS OBTAINED USING BOTH TONAL AND TEXTURE MEASURES

VERIFIED CLASSIFICATION \ COMPUTER CLASSIFICATION	DE	KN	WN	ST	HL	SCH	MS	LB	DB	CW	TOTAL	PERCENT CORRECT
DE	98	0	0	0	0	1	1	0	0	0	100	98.00
KN	1	76	1	0	5	1	0	1	1	0	86	88.37
WN	0	3	96	0	1	0	0	0	0	0	100	96.00
ST	0	0	1	92	0	2	0	3	0	1	99	92.93
HL	0	3	0	0	75	1	1	0	1	0	81	92.59
SCH	1	0	0	0	0	95	1	1	0	2	100	95.00
MS	3	0	0	1	1	2	93	0	0	0	100	93.00
LB	0	2	4	4	3	4	0	58	1	0	76	76.32
DB	0	7	3	0	15	1	1	2	39	0	68	57.35
CW	3	0	0	7	0	1	1	0	0	180	192	93.75
TOTAL	106	91	105	104	100	108	98	65	42	183	1002	
OVERALL PERCENTAGE CORRECT CLASSIFICATION												88.33

TONAL AND TEXTURE MEASURES

The results shown in Table II are not surprising given the capabilities of the Bendix system. This system employed measures related to the tonal qualities of the board. While the system could with human help separate clear wood from defects it could not classify the type of defect present.

Table III shows the accuracy obtainable when only the second-order texture measures defined in (5)–(10) are considered. Note that while the ability to identify the type of defect present is improved there is still room for significant improvement. Consider, for example, the stain class. Stain is a general darkening of the wood; a darkening which does not affect the nature of the wood grain. Consequently, the confusion between stain and clear wood when only the texture measures are used is understandable.

Table IV shows the classification results obtainable when both first-order tonal measures and second-order texture measures are used. Note the improvement in the overall percent of correct classification from both Tables II and III. Further observe that all but two of the defects were classified with better than an 88 percent classification accuracy. Only light bark and dark bark are low. Also notice that only 3 of 810 defect samples were incorrectly labeled as being clear wood, a 99.62 percent accuracy, while 93.75 percent of the clear wood samples were correctly classified.

While these results may not be high enough for all industrial applications (studies are only now being conducted to determine how well humans perform the task) they do suggest that a commercially useful system can be created. Such a system only requires a marginal improvement over the results thus far obtained. An obvious method for attempting to obtain this marginal improvement is by incorporating color information in the analysis process. Consequently, obtaining the required accuracy seems achievable.

The major problem remaining concerns the computational burden imposed in calculating the texture measures. Given this complexity one is forced to consider methods which minimize the computational load. A method involves a two-stage sequential classification scheme which first attempts to separate clear wood samples from those samples containing a defect. The second stage in the process is to classify the defect. The first stage requires only the calculation of the first-order measures. The second stage uses the first-order measures but also requires the calculation of the texture measures. The second stage employs the pairwise classification procedure used in obtaining the results in Tables II–IV.

The motivation for this sequential classifier comes from two sources. First, lumber grades used at a furniture mill are such that they guaranteed 80 percent or better of each board surface area is free of any defect. Secondly, Table II suggests that the computationally simple tonal measures can be used to separate clear wood from areas containing a defect very accurately.

The first stage of this scheme employs the chi-squared test defined in (11). Table V shows the classification accuracies obtained for two different values of T. Note these results given in Part (A) indicate that if one is willing to tolerate 2

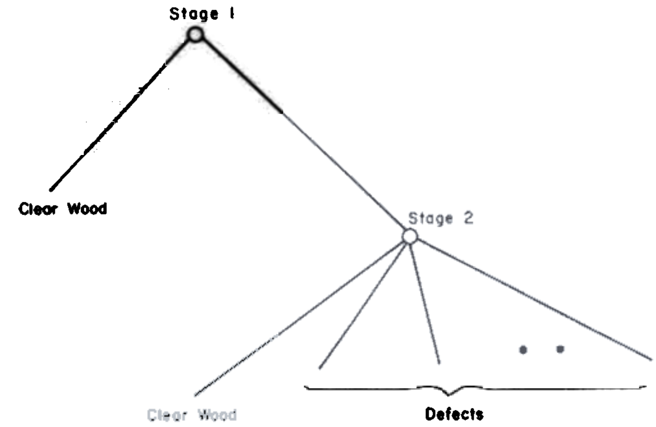
TABLE V
CLASSIFICATION ACCURACIES OBTAINABLE USING THE CHI-SQUARED TEST (11) TO SEPARATE THE CLEAR WOOD SAMPLES FROM DEFECTS. NOTE ONLY THE FIRST-ORDER MEASURES WERE USED IN MAKING THESE CLASSIFICATIONS. PARTS (A) AND (B) SHOW RESULTS FOR TWO DIFFERENT VALUES OF T.

VERIFIED CLASSIFICATION	COMPUTER CLASSIFICATION CW	DF	TOTAL	PERCENT CORRECT
CW	173	19	192	90.11
DF	17	793	810	97.9
TOTAL	190	812	1002	
OVERALL PERCENTAGE CORRECT CLASSIFICATION				94.01

(A)

VERIFIED CLASSIFICATION	COMPUTER CLASSIFICATION CW	DF	TOTAL	PERCENT CORRECT
CW	81	111	192	57.8
DF	3	810	810	99.6
TOTAL	84	921	1002	
OVERALL PERCENTAGE CORRECT CLASSIFICATION				78.7

(B)



SEQUENTIAL CLASSIFIER

Fig. 6. A sequential classification scheme which can be used to minimize the computational burden in solving the defect inspection problem.

percent of the defects being called clear wood then over 90 percent of the clear wood samples can be labeled using only first-order measures. Given that over 80 pecent of the board surface is defect free this means that over 72 percent of the regions can be classified using only tonal measures while only the remaining 28 percent require the calculation of the texture measures; a significant saving in computational complexity. Part (B) shows that if more accuracy is required the computational burden increases.

VII. Discussion

The results of the feasibility study indicate that an automatic surface defect inspection system can be created. Therefore what remains is to demonstrate the technical feasibility of the other system components as well as the economic motivation for ALPS.

A. Scanning System Technology and ALPS

The imaging system used in ALPS must be rugged and capable of withstanding the vibrations typical in an industrial environment. It must have a long mean time between failures. To meet production requirements, the system must be able to scan as many boards as possible in a given unit of time. This means the imaging device must have near zero lag. To preserve the precise spatial arrangement of the surface structure of the boards the device should have a small geometric distortion. To provide as much contrast as possible (given that only one scanner setting can be used) the system should have a large dynamic range. Finally, the system should preferably be commercially available; one not requiring any specialized design.

All these requirements point to a solid-state imaging device. The question becomes whether there exist commercially available solid-state devices with sufficient resolution. To address the resolution question one must consider the structure of hardwood lumber. The organization of the cellular structure of wood can best be understood from study of three surfaces—transverse, tangential, and radial. Fig. 7 shows a scanning electron micrograph of Shumard oak illustrating all three surfaces simultaneously in their proper spatial relationship [29].

The anatomical structure of interest in hardwoods are vessels—structures that conduct water within the stem that appear as large vertical tubes. Vessel openings in both earlywood and latewood are clearly visible on the transverse surface of Fig. 7, and vessel members may be seen on the tangential surface where vessels have been cut. Earlywood is that part of the annual ring produced in the spring, while latewood is formed towards the end of the growing season.

Of all the possible wood defects a check, i.e., a small crack in a board surface running parallel to the grain, has the smallest dimension. Consequently, the requirements on detecting checks dictate the resolution of the scanning system. The tangential plane forms the surface of most boards. As shown in Fig. 7 vessels appear as indentations in this surface, not unlike a small crack or check. An argument can be made that as the width of a check approaches the diameter of a vessel it becomes harder for the unaided human eye to see, and hence unimportant for the automatic system to detect. Vessels in red oak have a diameter of about 0.010 in. While vessel diameters vary considerably, 200 to 300 points/in would seemingly be an upper bound on the resolution required for the scanning system. Given that the boards entering the rough mill are rarely over 12 in wide a solid-state detector capable of obtain-

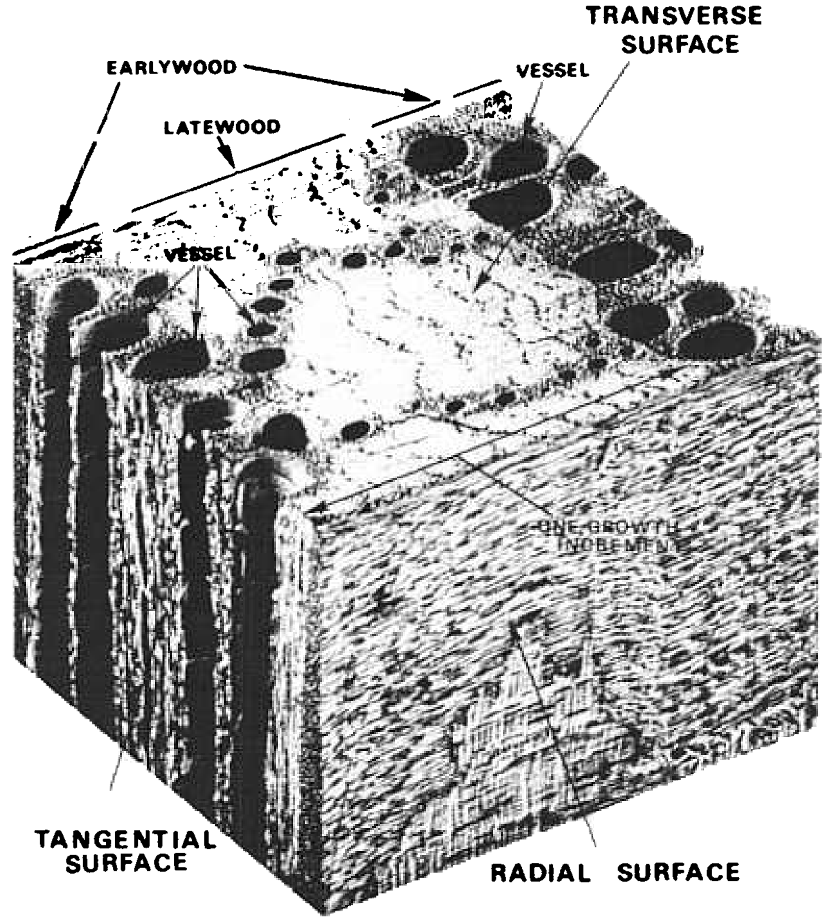


Fig. 7. Scanning electron micrograph of Shumard oak cube

ing 4096 points across the face of the board is adequate. There are a number of linear detectors which are or soon will be available with this resolution.

B. Computer Technology and ALPS

Computers are needed in the ALPS system to analyze digital image data, to compute an optimal strategy to cut the desired parts, and to control the conveyors and lasers used to move and cut the boards. Of these tasks, the most computationally complex are the image analysis function and the determination of the optimal sawing strategy.

A parallel processing approach seems the only viable computational method. The possibility of using it depends on the research and development time needed to create such a system. Seemingly, to make this approach practical requires that off-the-shelf hardware be available which only requires a minimum of system integration and that methods be available to program the resulting system in a higher level language in order to reduce software development cost. Software costs could easily comprise the majority of the total ALPS costs.

Given the ambiguity of the processing requirements, the technological assessment of computers capable of meeting ALPS requirements will be based on demonstrating a currently available processor which seemingly has all the desired properties. A processor of considerable potential is the Intel iAPX-432 microcomputer [31]-[35]. It represents the first of a new generation of microcomputers and seems ideally suited to processing requirements posed by an ALPS type system. It is programmed in Ada and has a packet bus structure which allows parallel processing to be employed in a user transparent fashion. If the past is any indication, marked improvements in processing power should become a reality within the next 4 to 5 years. Hence it seems that even if the initial iAPX-432 systems cannot meet the processing demands, improvements to this processor or ones marketed by other companies should.

C. Laser Technology and ALPS

For a laser cutting system to be practical it must be able to cut at a rate of approximately 100 ft/min of 1 in lumber. To determine whether a commercially available laser can cut lumber at this speed, equations developed by Peters and Banas [36] are helpful. Their study focused on factors affecting the cutting speed of lasers. They found that speed varies with species, board thickness, and laser power. For Douglas fir cut with a 5 kW laser, cutting speed could be expressed by the equations

$$\Delta = K_1/T^2 \tag{12}$$

where Δ is the cutting speed in ft/min, T is the wood thickness in inches, and K_1 is a constant. Further they found that

$$\Delta = K_2 P^{1.35} \tag{13}$$

where P is laser power in kW and K_2 is a constant. Combining (12) and (13) one obtains the expression

TABLE VI
ECONOMIC FACTORS WHICH FAVOR AN ALPS SYSTEM

1.) Lumber raw material
   a. Elimination or reduction of saw kerf loss.
   b. The possibility of substituting lower grades of lumber to produce the same products.
   c. Higher yields due to "punch-press" instead of cross-cut and rip saws.
   d. Improvement of quality of the products.

2.) Machine
   a. Elimination of several conventional machines.
   b. Reduction of maintenance due to tool wear.

3.) Energy
   a. Reduced electrical costs with laser cutting.
   b. Reduction of wood waste.
   c. Smaller space requirements due to a single machine substituted for six to twelve saws.
   d. Lower replacement air cost due to a smaller sawdust blower.

4.) Labor
   a. Effect of automation on labor cost.
   b. Effect of improved yield.
   c. Effect of safety.

$$\Delta = KP^{1.35}/T^2 \tag{14}$$

where K varies with species.

Using the values given in [32] for hickory, the wood found to be the most difficult for a laser to cut, one can solve for K in (14). The power required to cut 100 ft/min of 1 in lumber can be estimated using this constant. The estimate obtained is approximately 21 kW, a power just beyond the limits of what is presently commercially available although a number of companies have 20 plus kW lasers in their laboratories.

However, it is not clear the system should be designed to use only one laser. Using a multiple laser system is attractive not only from the point of view that existing technology can be used but the speed at which boards must be moved under the lasers can be reduced. This is important giving the right angle punch press type of operation required to give maximum yield. Secondly, having a system employing two or more lasers allows for continued operation of the system given a failure of one laser, albeit at reduced speed.

were ignored in this initial study. With this conservative approach, calculated savings for a furniture plant using red oak lumber were \$1210 per day and \$1198 per day when using sap gum.

The net present value of the laser investment was \$408 024 and the internal rate of return after tax was 22.5 percent. Both values would be considered an excellent investment opportunity in the financial community. Clearly, if the other savings in lumber, energy, and labor costs were included, the analysis would be even more positive in favor of the laser system.

VIII. SUMMARY AND CONCLUSIONS

This study indicates the technical feasibility of an ALPS system. The major hardware items needed in such a system are either currently being produced or will be available in the next 3 to 5 years. Further, there is a strong economic incentive to develop such a system.

The major problem is to create the necessary image analysis and pattern recognition methods to quickly and accurately locate, identify, and determine the extent of surface defects in lumber. While the accuracies which were obtained are not up to industrial requirements they do indicate that with continued research such accuracies should be obtainable. For example the incorporation of color information into the inspection process holds the potential for substantial improvement in differential defect identification accuracies.

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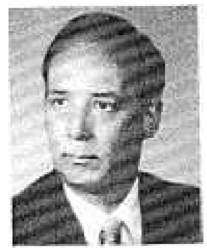

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