ABSTRACT. Machine vision and automated processing systems are under development at Virginia Tech University with support and cooperation from the USDA Forest Service. Our goals are to help U.S. hardwood producers automate, reduce costs, increase product volume and value recovery, and market higher value, more accurately graded and described products.

Any vision system is composed of two bread tasks: image scanning and image interpretation. A rough lumber vision system recognizes board defects, clear wood, and board outlines, and labels these areas. Two available computer programs can use this defect information. The first program grades the board by National Hardwood Lumber Association grading rules. The second program simulates the processing of the board into standard or specific cuttings or part sizes by two different cutup methods. One goal of the vision system is to analyze images of rough lumber in a species-independent manner.

A second machine vision system deals with log scanning. This system is being developed to recognize log defects, clear wood, and log outlines and to label defect areas. This information can help sawmill operators sort logs as veneer or sawlogs, crosscut long roundwood into logs, determine how to flitch a veneer log for slicing, and determine processing for a sawlog.

Machine Vision Systems for Processing Hardwood Lumber and Logs

Philip A. Araman,[1] Daniel L. Schmoldt,[1]
Tai-Hoon Cho,[2] Dongping Zhu,[2]
Richard W. Conners,[2] and D. Earl Kline[3]
Virginia Polytechnic Institute and State University
Blacksburg, Virginia 24061

Hardwood timber is a substantial economic staple in the eastern U.S. Primary hardwood processors there produce more than 10 billion board feet of sawn hardwoods annually. Most of their facilities are not large (i.e., less than 10 MMBF/year) and are located in rural areas. Therefore, the survival of this industry is important for the economic well-being of many communities.

The manufacture of furniture, cabinets, flooring, millwork, and moldings, along with hardwood exports, accounts for most of high- and medium-grade hardwood lumber consumption. There are several steps in processing hardwood logs into these final products (Fig. 1). Roundwood is transported from the woodlot to the sawmill. Logs are then separated into veneer logs and sawlogs. Veneer logs are shipped to veneer mills where they are sawn into flitches and then sliced to produce veneer. Sawlogs are processed into boards of standard thickness. After kiln drying, boards are sent to a dimension mill where they are processed into furniture/cabinet parts, flooring, or moldings. Final cutting, milling, gluing, staining, and assembly occur at plants dedicated to specific final products. Much of the cooperative work in this area at Virginia Tech deals with two aspects

[1] USDA Forest Service, Southeastern Forest Experiment Station, Brooks Forest Products Center.
[2] Bradley Department of Electrical Engineering.
[3] Department of Wood Science and Forest Products.

of manufacture: (1) primary processing and (2) lumber grading and analysis.

Hardwood sawmiller face several difficult situations. First, demands for hardwood lumber for domestic and export markets vary widely from year to year. Since 1985, annual demand has been as high as 11.4 billion board feet and as low as 8.8 billion board feet (National Forest Products Association 1991). Second, a majority of the available material in the woods is low grade, while customer needs are for high grade lumber. Third, inconsistent product quality and less than optimal processing are problems for many producers. And fourth, log costs have been increasing faster than lumber prices. These circumstances dictate that sawmill operators become more efficient and improve their use of available raw materials.

In recent surveys (Bush 1989, Bush et al. 1990), hardwood lumber customers reported several major concerns: (1) inaccurate lumber grading by producers, (2) inconsistent lumber thickness, and (3) poor quality of the purchased lumber. To keep and satisfy hardwood lumber

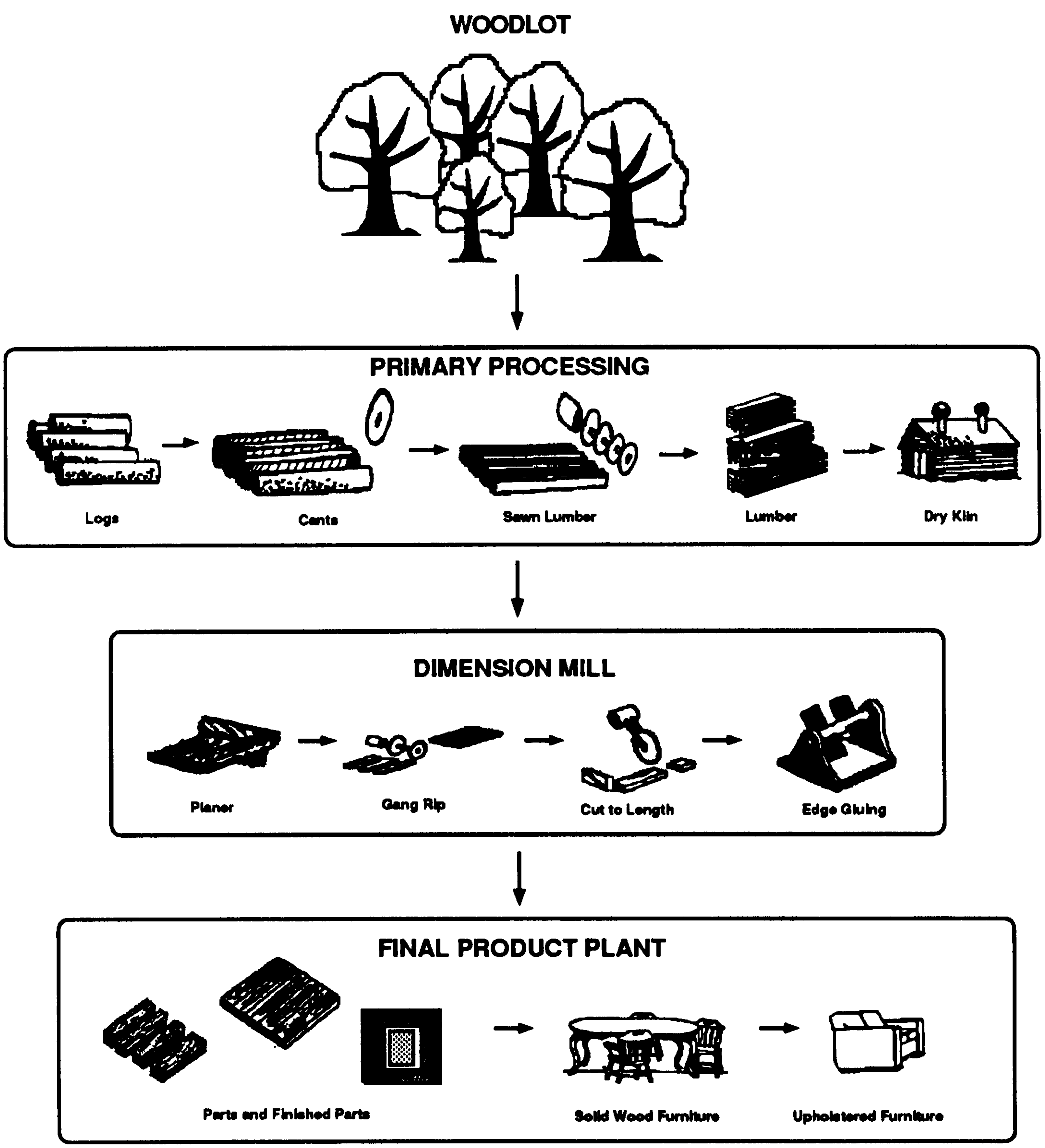


Figure 1.
The manufacture of hardwoods into finished products takes place in several different mills. A typical manufacturing scenario is depicted here. The particular manufacturing operations performed at a specific mill are dependent on a company's facilities and the type of finished products made.

customers, hardwood sawmiller need to improve the accuracy of their lumber grading and provide consistent, high-quality products. They also need to get more value out of the logs they are processing.

Vision may be more tightly integrated with intelligence than any other sensing modality. More than one-fourth of the brain's volume is dedicated to vision activities (Tanimoto 1987). There is some evidence to indicate that much of our thinking is augmented by visualization (Kosslyn and Schwartz 1978). New computer interfaces, virtual realities, and visualization tools are emerging from that premise.

Image processing techniques have been around for some time. Basically, they include: image formation, sensing, preprocessing, segmentation, and description (Tanimoto 1987). All of these steps can be accomplished using traditional mathematical and statistical methods exclusively. That does not mean that these systems are not AI. In fact, because they deal with the problem of capturing an image and interpreting its contents, they are by definition AI, regardless of the technical methodologies employed.

Machine vision systems and computer-aided processing systems hold promise for solving the problems of hardwood sawmiller. Automated systems could improve product recovery, increase productivity, improve raw material utilization, reduce costs, improve marketing, and accurately grade lumber. Research projects described here are designed to help the U.S. hardwood sawmill industry realize these potentials. These projects are team efforts that concentrate on computer-aided processing. This report focuses mainly on machine vision systems for rough lumber and for logs.

Machine Vision and Automated Grading/Analysis of Hardwood Lumber

Developing automated systems for lumber grading and describing potential furniture cuttings in hardwood lumber are the goals of this research. A key to the success of this work is the ability to automate the detection of defects on boards. Defects must be located, properly sized, and identified. Lumber grade for aboard can be improved by edging and trimming the board. Software can be used to select the edging and trimming lines to maximize board value. Then computer programs can grade the boards and determine the possible furniture cuttings in them. In most secondary hardwood processing mills, boards are either cut along their length (rip first) or cut across their length (crosscut first) as a first cutup operation. Both options normally are not available. The complementary cuts needed to get clearwood cuttings and to remove defects normally are made in subsequent operations. One of the biggest advantages of automated computer scanning can be realized if the choice of ripping or cross-cutting first is based on the characteristics of individual boards and their defects.

> MACHINE VISION AND COMPUTER-AIDED PROCESSING SYSTEMS HOLD PROMISE FOR SOLVING MANY OF THE PROBLEMS OF HARDWOOD SAWMILLERS.

A system composed of scanning, grading, and analysis would generate packages of computer-graded and marked lumber. Information on individual boards and entire packages of lumber would accompany shipments of lumber. Grade mix, total board footage, potential yield in cuttings, and potential distribution of cuttings could be shown as in the tally sheet in Figure 2. Yields in specific or standard-sized cuttings could be determined for both rip-and crosscut-first rough mill processing. The supplier could then sort and package lumber for these two rough mill options. The output information shown in Figure 2 could be changed or expanded as needed.

For a number of reasons, the machine vision system is the most difficult component to design and is taking the longest to develop. First, a grading system must be able to handle a variety of species. Hardwood species vary substantially in their appearance and in the way undesirable feature manifest themselves. Further, for an automated system to be industrially useful it must process lumber at least as fast as a skilled human grader. This means that the vision system must be able to analyze image data at a rate of at least two linear feet per second, and grade a 16-foot board in eight seconds. Last, because grading depends on detecting small defects, the vision system must process high spatial resolution image data. To satisfy these needs, we have had to abandon off-the-shelf machine vision systems in favor of developing a system using special purpose methods.

Basic research on detecting, sizing, and identifying wood defects on rough and surfaced lumber by machine vision is underway. Defect detection on *rough* lumber is similar to detection on *surfaced* lumber, but it is much more complex. Surfacing lumber removes many of the visual characteristics of wood that confound the identification of surface features (Conners et al. 1989). Lumber changes in visual appearante as the surface dries. Outside storage and drying can cause color changes due to weathering and ultraviolet light. Handling and storing of wood can introduce dirt onto its surface. The roughness of the wood surface creates shadows that alter visual appearance. Planing boards would take care of most of these problems, but hardwood is mostly graded and traded before surfacing. So, we need to scan and grade rough rather than surfaced lumber.

Several computer programs are now available to make use of machine vision information on defects and board outlines. One program grades hardwood lumber (Klinkhachorn et al. 1989) by the standard rules of the National Hardwood Lumber Association (NHLA). Another computer program, CORY (Brunner et al. 1989), determines the potential cuttings in each board. The latter program also compares the yields in cuttings for cross cutting or ripping the board as the first cut-up process. A third program has been developed to help sawmills properly edge, trim, and grade wane-edged sawmill flitches (Regalado 1991). These computer programs are useful now, and by integrating them with a machine vision system, a completely automated system (Fig. 3) can introduce greater processing efficiency and accuracy with enhanced wood utilization.

With the above capabilities, lumber producers could provide the accurately and consistently graded material desired by secondary processors. End users could verify lumber grades from supplying mills that do not use the machine vision system. Hardwood lumber users could apply the system to determine which boards should be crosscut or ripped first and to aid in the actual lumber cutup operation. Information on potential furniture cuttings could help determine the proper lumber grade or grade mix that should be used for different situations.

EXAMPLE TALLY SHEET FOR THE COMPUTER ANALYZED LUMBER

BATCH INFORMATION		GRADE MIX	
SOURCE	HARDWOOD CO.	FAS	5%
SPECIE	RED OAK	SEL	3%
LENGTHS	9 & 10	1C	67%
THICKNESS	5/4	2C	25%
TOTAL BD FT	1500 BD FT	3C	
DATE	7-17-91		

POTENTIAL YIELD IN:
X STANDARD LENGTHS
— SPECIFIC LENGTHS
(LENGTHS ARE DISPLAYED IN GRAPH BELOW)
(WIDTHS ARE RANDOM)
IS 78%

DISTRIBUTION OF POTENTIAL CUTTINGS BY LENGTH

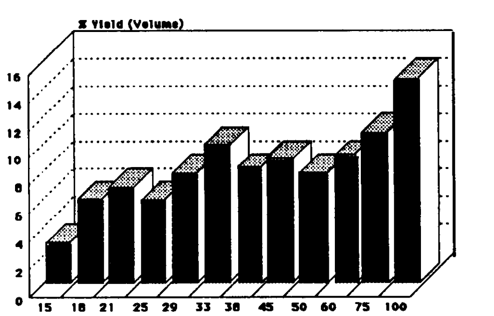


Figure 2.
An example tally sheet and the companion graph of cutting lengths for computer analyzed lumber illustrates the type of information that can easily be provided for each package of lumber using an automated system.

Machine Vision and Automated Processing of Logs

Determining the location, type, and shape of defects within logs, would permit automated processing of logs into lumber, rough green parts, or veneer. Defect information would improve three important preprocessing decisions: (1) how to convert tree-length roundwood into logs, (2) whether to process a log into veneer or lumber, and (3) how to maximize value yield from a lumber sawlog. To do this, the log must be scanned in some manner, the scan information must be interpreted, and a three-dimensional rendition of the log must be created. Bucking, processing, or sawing decisions may then be based on this visual image of the log or, alternatively, further analyses can determine the optimal sawing method without human intervention.

Tree-length roundwood needs to be processed into logs before further processing into lumber or veneer. If the locations and shapes of internal defects are known, it is possible to cut roundwood into logs while removing major defects. This leaves greater areas of valuable clear wood in the remaining log, and gives it higher value. At the same time, certain logs can be identified as veneer quality, which would increase log values by a factor of 10 or more.

Even after defects have been located, the choice of a cutting pattern for a log is complex. Many research articles have reported results of different log cutup methods and their impact on lumber produced (q.v. Harless et al. 1991). We are conducting cooperative studies to determine the optimal sawing strategies for maximizing both volume and value recovery from logs.

To convert medium- and low-grade logs into end products more effectively, we are conducting research to produce green rough dimension material (blanks) directly from logs. Blanks can be either cut-to-length, random-width dimension stock with defects removed or standard width strips that will be cut to length and have defects removed after drying. Presently, mills process many of these logs into low-and medium-grade lumber. This lumber is dried prior to processing into blanks. By producing green (undried) blanks, we are eliminating the drying of defect areas of the lumber. Automated scanning is an important aid to help make better sawing decisions when producing green blanks.

Scope and Status of the Vision System for Logs

We are studying methods for locating and identifying internal defects in logs. Machine vision of logs incorporates the image scanning and interpretation techniques used for lumber, but there are two important differences. First, we must represent and analyze defects as three-dimensional objects. Scanning captures and stores images as two-dimensional slices, and much of the image analysis takes place with these slices. The image interpretation step creates time-dimensional images by reconstructing a sequence of two-dimensional images, or slices, of a log. Second, machine vision of logs detects internal features. Development will be difficult and time consuming because scanned logs must eventually be cut up to verify the existence, location, and size of defects that the machine vision system has "seen."

Image Scanning of Logs

The internal structure of a log can be inferred by measuring attenuation of x-ray transmissions through the log. X-ray transmission can be measured by locating linearly arranged banks of x-ray emitters and detectors on opposite sides of a log. Each emitter-detector pair represents a ray of radiation. The x-ray attenuation along that ray is the summation of the attenuation by each small volume in the ray's path. By wording detector values and rotating the emitter-detector banks through a small angle and then continually repeating this process through 180°, one can calculate an attenuation value for each small volume of the log in this plane. Each "slice" taken in this manner is a tomograph and the process is referred to as computed tomography (CT). Each pixel in this CT image has an associated CT number. CT numbers typically range from -1024 to 1024, where water has a value of 0. X-ray attenuation is dependent on density; therefore, CT numbers rep resent density measurements.

Purchase and maintenance of an x-ray scanning system with the power and size to image logs would be very expensive. Consequently, often a cooperative arrangement must be established with some facility, such as a hospital radiology department, to perform scanning. Unlike optical imaging of lumber, where the required technology must be developed, we can readily apply x-ray CT scanning using off-the-shelf systems. Alternative materials-handling devices for use with logs must be designed and built, however. It is likely that less resolution will be needed for forest products applications than that used in medicine. This will reduce the cost of image reconstruction from detector values and will permit the use of less powerful, less expensive, and safer radiation sources (Zhu et al. 1991a).

Some of our early machine vision work on logs used CT images taken from a single red oak log 12 feet long. This sequence of 256 by 256 cross-sectional slices consisted of 480 digital images of 12-bit CT values. The total amount of data for a log of this size is about 47 MB. To capture and process this amount of data in real time requires very fast computer hardware (Kenway 1991). Recently, we have scanned “interesting” portions of logs (sections containing defects) of red oak and yellow poplar (Zhu et al. 1991c). We are using this database of CT images and their corresponding ground-truth photographs to create species-independent image interpretation software.

Image Interpretation of Logs

Image interpretation again will include segmentation and recognition. For log scanning, however, we must focus more attention on filtering the initial image before segmentation. Wood density varies frequently through a log slice, whereas color variation is much less frequent on lumber surfaces. In particular, annual rings are detected by x-rays. This unwanted detail confounds the image interpretation task (Zhu et al. 1991a). So, CT scanning (at the resolution used in medical applications) detects much variation in wood structure that is unimportant for actually locating and identifying defects.

Zhu et al. (1991a) developed a special three-dimensional filter for this work. It removes high frequency signals, such as annual rings, by using information from successive slices. Figure 6 illustrates the impact that this three-dimensional filter has on segmentation. An unfiltered image (Figure 6b) after segmentation contains thousands of spurious objects that must be identified in the recognition step. Filtering leaves only a few objects needing identification in the recognition phase (Figure 6c). Without substantial filtering, defect recognition would not be possible for segmented images such as Figure 6b.

Segmentation and recognition analyses are applied to each slice individually. However, because the objects that must eventually be identified are three-dimensional, consecutive CT images are used in a three-dimensional, volume-growing algorithm to segment regions on a single image. The recognition system uses the following pieces of information to make a heuristic classification of objects (Zhu et al. 1991b): (1) mean and standard deviation of the CT values for an object, (2) texture information about how CT values are spatially distributed throughout an object, (3) shape of an object, and (4) radial location of an object. Figure 7 illustrates some of the capabilities of the current segmentation and recognition steps. The original CT image “slice” appears in Figure 7a. Results from the segmentation step appear in Figure 7b. Recognition results appear in Figure 7c. The recognition system can currently distinguish four defect types from clear wood—bark, knots, holes, and splits. Both the segmentation and recognition algorithms are still under development.

Once defects are located and identified on each slice, their slice perimeters can be used to reconstruct a three-dimensional solid representing each defect’s appearance in the log. Computer programs, now under development, can then use this information to simulate the log sawing operation, to make processing decisions about the optimal way to saw a log, and to provide visual information for a saw operator.

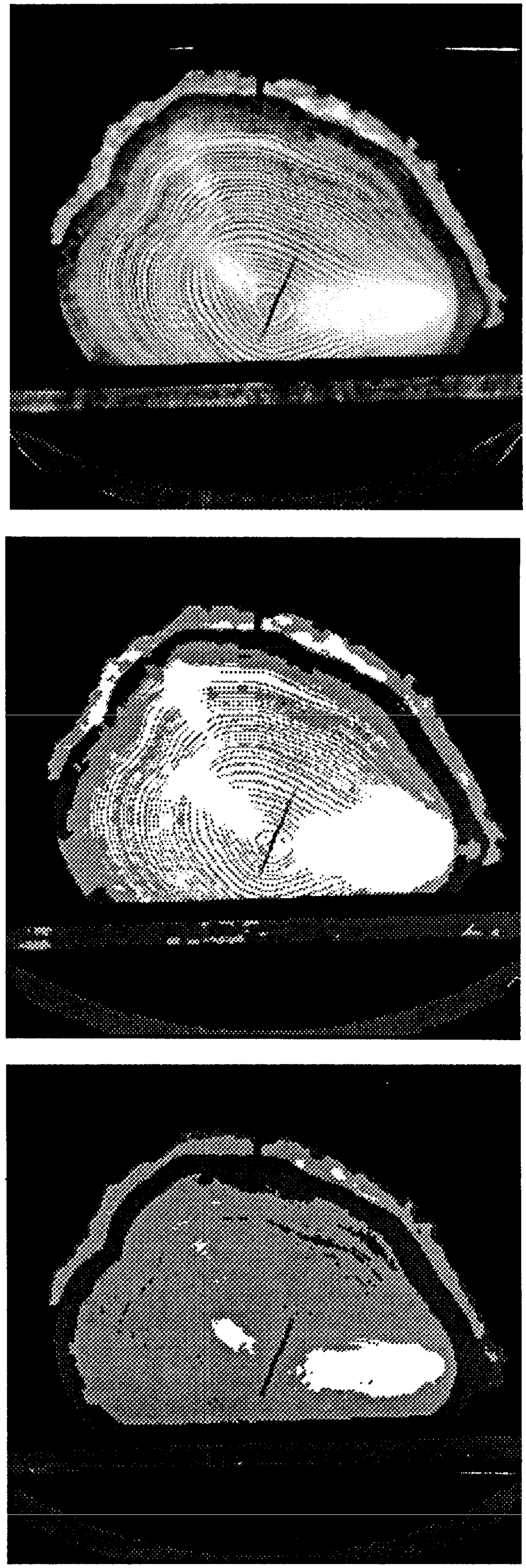
Discussion and Conclusions

Cooperative research by scientists with the USDA Forest Service and Virginia Tech University has clearly shown that automated scanning of both rough lumber and logs is possible. Serious questions remain about whether it will be practical for typical sawmilling operations, but we are optimistic. Our costs have been high because we are breaking new ground in a research-oriented operation. For example, equipment costs alone for the rough lumber vision system are approximately $200,000. An industrial CT scanner for logs will be more than $500,000. Once the vision systems are perfected, however, we think that machinery manufacturers will be able to transform our research into saleable products.

As we proceed toward a fill-scale prototype for grading and analyzing lumber, processing speed becomes increasingly important. At present we can scan at acceptable industrial speeds, but we will have to increase our computing speed substantially to process the large amounts of data gathered in scanning. At present, initial processing algorithms consume about two-thirds of image-processing time. By converting the vision system from FORTRAN to C and improving program data structures, we have doubled the speed of our image processing. Nevertheless, new algorithms and faster computers must be used to approach industrial speed.

We are still years away from practical imaging of logs. Costs of getting CT image data are a major problem. Previously, we only had data on a single red oak log, and robustness of the approaches was open to question. Recently, we acquired data on other species, which we are now analyzing.

While we are enthusiastically developing vision systems for detecting a wide array of wood defects, we are aware of the costs that are associated with the systems we develop. Information costs money, and the more detailed the



A

B

C

Figure 6.
(A) A 256 x 256 slice of a red oak stem illustrates CT image detail. (B) Segmentation of the unfiltered CT image produces many regions. (C) Segmentation of the filtered CT image produces far fewer regions than with the unfiltered image.

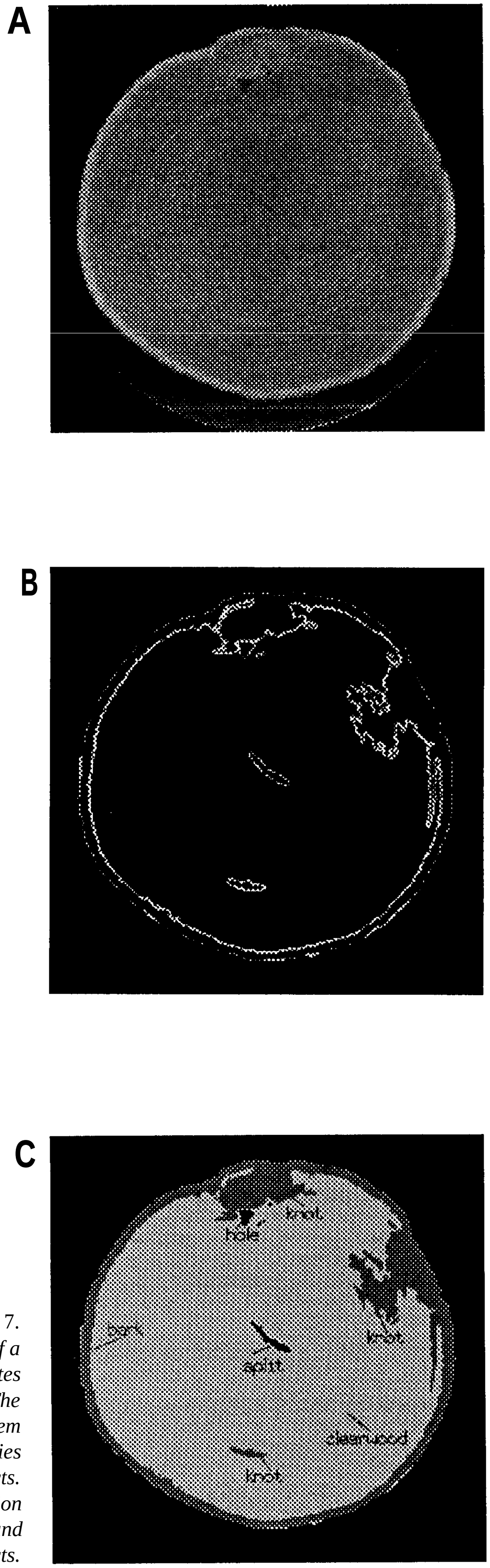


Figure 7.
(A) A 256 x 256 slice of a red oak stem illustrates CT image detail. (B) The segmentation system produces boundaries around bark and defects. (C) The recognition system identifies and labels various defects.

information, the higher the costs, but the added cost is often justified. Regalado et al. (1992), for example, showed that in hardwood sawmills, when edging and trimming boards, a computerized system can achieve 80% of the optimum value by using only edge wane information. This is substantially higher than current mill recovery rates. They also found, however, that by using the size and location of all defects (without knowing the type of defect), they could increase the recovery rate to 95% of optimum. Thus, even small increases in the amount of information available, if carefully applied, can substantially enhance productivity.

We recognize that producer and consumer preferences can influence the value of lumber and other wood products. Individuals may favor particular attributes of lumber that have little or nothing to do with standard lumber grading rules. For example, NHLA lumber grading rules do not include wane as a defect and allow a large amount of wane on high quality boards. Nevertheless, many buyers have a strong bias against heavily waned boards due to visual preference and the need to remove wane in subsequent processing. Our machine vision and automated processing systems must be flexible enough to accommodate such market realities.

When our systems are perfected, they are likely to be applied to a broad array of forest product manufacturing situations. Even if they are not installed in a particular mill, they could be used ingraining of that mill's operators. They could also be used to grade and sort pallet parts, sorting those of the highest grade for long-use pallets. These are just a few additional potential uses for machine vision systems in hardwood lumber and log processing.

References

Brunner, C. C., M. S. White, F. M. Lamb, and J. G. Schroeder. 1989. CORY: A computer program for determining dimension stock yields. Forest Products Journal 39(2): 23-24.

Bush, R. J. 1989. Business-level competitive strategy in the United States hardwood lumber industry. Ph.D.

dissertation, Virginia Polytechnic Institute and State University, Blacksburg, Virginia.

Bush, R. J., S. A. Sinclair, and P. A. Araman. 1990. Match your hardwood lumber to current market needs. Southern Lumberman 251(7): 24-25.

Bush, R. J., S. A. Sinclair, and P. A. Araman. 1990. Matching your hardwood lumber to market needs. Southern Lumberman 25 1(8): 24-27.

Cho, T. H. 1991. A knowledge-based machine vision system for automated industrial web inspection. Ph.D. dissertation, Virginia Polytechnic Institute and State University, Blacksburg, Virginia.

Cho, T. H., R. W. Connors, and P. A. Araman. 1990. A computer vision system for analyzing images of rough hardwood lumber. Pages 726-728 in: Proceedings, 10th International Conference on Pattern Recognition June 16-21, 1990, Atlantic City, New Jersey.

Cho, T. H., R. W. Connors, and P. A. Araman. 1991. A comparison of rule-based, k-nearest neighbor, and neural net classifiers for automated industrial inspection. Pages 202-209 in: Proceedings, IEEE/ACM International Conference on Developing and Managing Expert System Programs, September 30-October 2, 1991, Washington, D.C.

Conners, R. W., T. H. Cho, and P. A. Araman. 1989. Automated grading of rough hardwood lumber. Pages XVI-1-15 in: Proceedings, 3rd International Conference on Scanning Technology in Sawmilling, October 5-6, 1989, San Francisco, California.

Harless, T. E. G., F. G. Wagner, P. H. Steele, F. W. Taylor, V. Yadama, and C. W. McMillin. 1991. Methodology for locating defects within hardwood logs and determining their impact on lumber-value yield. Forest Products Journal 41(4): 25-30.

Kenway, D. J. 1991. A supercomputer-based machine vision grading system and trimmer optimizer for dimension lumber. Pages 53-66 in: Proceedings, FPRS Southeastern Section Annual Meeting, T. Faust, editor. October 31, 1990, Athens, Georgia.

Klinkhachorn, P., J. P. Franklin, C. W. McMillin, R. W. Comers, and H. A. Huber. 1988. Automated computer grading of hardwood lumber. Forest Products Journal 38(3): 67-69.

Kosslyn, S. M., and S. P. Schwartz. 1978. Visual image as spatial representations in active memory. Pages 223-241 in: Computer Vision Systems, A. R. Hanson and E. M. Riseman, editors. Academic Press, New York.

National Forest Products Association. 1991. Statistical Round-up Quarterly Statistical Supplement, August 1991, Washington, D.C.

Regalado, C. 1991. Optimization of edging and trimming operations for red oak lumber. M.S. thesis, Virginia Polytechnic Institute and State University, Blacksburg, Virginia.

Regalado, C., D. E. Kline, and P. A. Araman. 1992. Value of defect information for automated edger and trimmer systems. Forest Products Journal 4(3): 29-34.

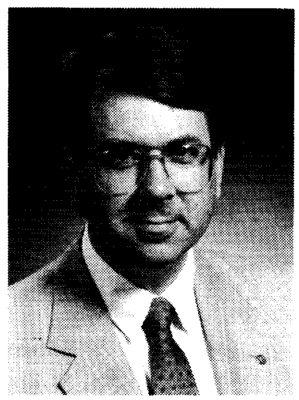
Szymani, R., and K. A. McDonald.1981. Defect detection in lumber: State of the art. Forest Products Journal 31(1 1): 34-44.

Tanimoto, S. L. 1987. The elements of artificial intelligence. Computer Science Press, Rockville, Maryland.

Zhu D., R. W. Conners, and P. A. Araman. 1991a. CT image sequence processing for wood defect recognition. Pages 75-79 in: Proceedings, 23rd Southeast Symposium on Systems Theory, March 1991, Columbia, South Carolina.

Zhu, D., R. W. Conners, D. L. Schmoldt, and P. A. Araman. 1991b. CT image processing for hardwood log inspection: a rule-based recognition system. Pages 173-178 in: Proceedings, IEEE International Conference on Systems, Man, and Cybernetics, October 1991, Charlottesville, Virginia.

Zhu, D., R. W. Conners, F. M. Lamb, D. L. Schmoldt, P. A. Araman. 1991c. A vision system for locating and identifying internal log defects using CT imagery. Pages 1-13 in: Proceedings, 4th International Conference on Scanning Technology in Sawmilling. October 28-30, 1991, San Francisco, California.



Philip A. Araman is a project leader with the Southeastern Forest Experiment Station at the Brooks Forest Products Center, and a senior research scientist at Virginia Tech. He has degrees from Paul Smith's College (forestry), North Carolina State University (wood technology), and Virginia Tech (forest products). Araman has a research mission to increase U.S. competitiveness by developing automated primary hardwood processing technologies and by developing new or improved products ma& from low-and medium-grade hardwood sawtimber and nonselect species. He has extensive experience in international trade of hardwood products and in the processing of hardwoods into furniture and cabinet products.

Daniel L. Schmoldt is a research forest products technologist with the Southeastern Forest Experiment Station at Virginia Tech. He received degrees in mathematics, computer science, and forest biometry from the University of Wisconsin-Madison. Prior to coming to Virginia Tech, he worked as a research forester for the Fire Management Planning and Economics project and the Atmospheric Deposition project of the Pacific Southwest Research Station. His current responsibilities involve research and development of computer-aided manufacturing systems

in the area of primary hardwoods processing. He is also interested in computer vision, pattern recognition, neural networks, and heuristic process control.

Tai-Hoon Cho received a B.S. degree in electronic engineering from Seoul National University, Korea in 1981, and an M.S. degree in electrical engineering from the Korean Advanced Institute of Science and Technology, Seoul, Korea, in 1983. He received a Ph.D. degree in electrical engineering from Virginia Tech in 1991. Since then, he has been a research scientist at the Spatial Data Analysis Laboratory. His research interests include computer vision, image processing, neural networks, pattern recognition, and AI.

Dongping Zhu obtained a B.S. degree in radio electronics and an M.S. in communications and electronics systems in 1982 and 1985, respectively, from Dalian University of Technology, Dalian, People's Republic of China. From 1985 to 1987 he was with the Department of Electrical Engineering at Dalian University of Technology as research associate and later as instructor. In 1989, he obtained an M.S. in electrical engineering from Virginia Tech. Since 1987, he has been a project assistant in the Spatial Data Analysis Laboratory at Virginia Tech, working towards a Ph.D. in electrical engineering. He is now employed as a staff imaging scientist with Imatron Industrial Products, Inc., Foster City, California. His major research interests include computer vision, pattern recognition expert systems, image processing and analysis, image texture modeling, digital and statistical signal processing, system theory, and their industrial applications.

Richard W. Conners received a Ph.D. degree in electrical engineering in 1976 from the University of Missouri-Columbia. In 1987 he Joined the Bradley Department of Electrical Engineering at Virginia Tech, where he is now director of the Spatial Data Analysis Laboratory. His research interests include computer vision, industrial automation, AI, and neura lnetworks. His interests in the industrial automation area center around the automation of segments of the forest products industry.

D. Earl Kline is currently an assistant professor with the Department of Wood Science and Forest Products at Virginia Tech. He received both B.S. and M.S. degrees at Virginia Tech and a Ph.D. degree at Texas A&M University in agricultural engineering. His past experience has included optimization and management of agricultural machinery systems, reliability methods in the design of timber structure, and the application of knowledge-based systems in agriculture. Current responsibilities involve research in the area of industrial systems engineering, process control, and process automation relating to wood and wood products processing. He is applying machine vision, computer simulation mathematical programming, and knowledge-based systems in these research areas.

SUBSCRIPTION INFORMATION

AI Applications is published quarterly in January, April, July, and October. Prepaid individual subscriptions $37; government agencies, university departments, libraries, private companies, and foreign subscriptions (including Canada) US$72 (US$16 extra optional for air mail to foreign addresses). Send subscription requests to: AI Applications, P.O. Box 3066, Moscow, Idaho 83843 USA (telephone 208/885-7033, fax 208/885-6226). Back issues are also available. Please write for information.