A Computer Vision System for Locating and Identifying Internal Log Defects Using CT Imagery

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Abstract

A number of researchers have shown the ability of magnetic resonance imaging (MRI) and computer tomography (CT) imaging to detect internal defects in logs. However, if these devices are ever to play a role in the forest products industry, automatic methods for analyzing data from these devices must be developed. This paper reports research aimed at developing a computer. vision system for locating and identifying internal defects in hardwood logs using CT imagery. This vision system can conceptually be divided into three components: a CT scanner based image acquisition system, a low-level module for image segmentation, and a high-level module for defect recognition. The processing steps involved in this vision system include CT data collection, image segmentation, three-dimensional volume growing, and a rule-based expert system for defect recognition. To date, progress has been made on all these processing steps though the work on developing a rule-based expert system is really just getting underway. Experimental data will be presented to show the progress that has been made on this vision system development.

I—Introduction

A number of investigators have shown that magnetic resonance imaging (MRI) [2] and computer tomography (CT) imaging [4][5][8] can be used to detect internal defects in logs. However, if this technology is to ever be used by the forest products industry, automatic methods for locating and identifying internal log defects must be developed. This paper reports research aimed at developing a computer vision system for locating and identifying internal defects in hardwood logs using CT imagery.

There are a number of reasons for wanting to locate internal defects in logs. First, tree-length roundwood may need to be cut prior to further processing into lumber or veneer. With internal defect information, it becomes possible to cut roundwood so that all defects are either removed or are isolated so that they appear at either end of the cut log section. This leaves larger areas of valuable clear wood in the log, and gives it a higher value. Second, it must be decided whether a log is a saw log or a veneer log. Since a veneer log is worth approximately ten times as much as a saw log, it is very important that this decision be made as accurately as possible. Whether a log is a saw log or a veneer log depends on the number and distribution of its internal defects. If the decision is to saw the log into lumber, studies [6] have shown that the value of the lumber sawn from a log can be increased from seven up to twenty-one percent if optimum positioning is used during saw up. Optimum positioning depends on the location and identification of internal log defects. The basic goal in sawing hardwood lumber is to create boards with as much clear face as possible. While no formal studies have been conducted, positioning also would seem to play an important role in determining the value of veneer that can reproduced from a veneer log. Once again the best positioning is the one that gives veneer with as much clear face as possible.

A nondestructive way to infer internal log structure is to use either MRI or CT systems to image the internal structure of logs. While both of these systems have their advantages and disadvantages, concentration here will be paid to CT imagery. There are a number of reasons for wanting to concentrate on CT imagery. First, CT imaging systems are less expensive than MRI units and will probably stay so well into the future. CT units do not require the expensive superconducting magnet required by MRI units. Next, CT units are seemingly “safer” to use in the sawmill or veneer plant. The magnetic field required by MRI units can pull any magnetic material out of a log as it is being imaged. If this happens serious damage to the superconducting magnet would most certainly occur. The magnetic field induced around the “outside” of the magnet is also very intense. Care would have to be taken not to get any iron or steel tools too close to the MRI unit or they to could be drawn toward the superconducting magnet.

Just as in the case of MRI, collecting CT imagery of a log is currently very expensive. Most available CT scanners are located in hospitals, and these units cost at least $600,000 apiece. Given the current high cost of medical CT units, the economic viability of using these systems on forest products applications must be a concern. However, there area number of good reasons to believe that the cost of industrial inspection versions of these machines will go down in the future. First, a significant percentage of the total cost of a CT machine is the cost of the computer and special purpose hardware used to do the reconstruction. Intel Corporation estimates that a bench mark microprocessor by the year 2000 will be able to execute 2 billion instructions per second, a 100 fold increase over the performance of today's benchmark processors. Further memory costs are continuing to decline in what appears to be a trend for all the 1990's. Hence, the cost of the processing units required to both reconstruct CT images as well as perform the automatic analysis should markedly decrease in the years to come. Another significant cost component in today's units is the research and development (R&D) cost. Current units are aimed almost exclusively at the medical market, a highly competitive market of very limited size. Given a relatively high volume market, such as the one that would be associated with the hardwood forest products industry, the R&D cost could be spread over a larger number of machines and hence the R&D cost per machine should be substantially lower. Hence there are reasons to believe that within the next decade CT seamers may become inexpensive enough to be applied to a number of industrial inspection problems including locating and identifying defects in hardwood logs.

CT imaging of a hardwood log along its length produces a stack of cross-sectional slices representing the three-dimensional structure of the log. The gray level value of each picture element (pixel) of a CT image is called its CT number. CT numbers typically range from -1024 to 1024 (12 bits of image data for each pixel). The CT number represents the calculated attenuation of the volume represented by the CT pixel to x-ray transmission. For this reason some investigators call CT picture elements "voxels" instead of pixels. The CT number of "0" typicall y corresponds to the attenuation of water. Since a material's x-ray attenuation is dependent on the material's density, CT numbers represent density measurements of the various structures within a log. CT images (slices) can have a variety of different resolutions. The resolution depends not only on the number of pixels appearing in the imaging plane but also on the "thickness" of the imaging plane. To give one an idea of the amount of data that can be created during the examination of a log suppose that 256x256 pixels are collected in the imaging plane and suppose that the imaging plane thickness is 8 millimeters. At this resolution a log section 10 feet long will generate approximately 47 megabytes of image data.

Although scanner cost is a problem in terms of the economic viability of CT scanners in sawmills, perhaps the most serious technical difficulties are image acquisition time, image reconstruction time and automated analysis processing time. Since a rate of three logs per minute is not uncommon in many sawmills, little time is available for acquiring, reconstructing, and processing an extremely large amount of image data. The amount of information that must be processed is a major problem for both present human operators and for any future automatic system. A very important recent development with regard to image acquisition has been the scanning electron beam CT scanner created by Imatron, Corporation [8]. In its ultrafast mode, the Imatron CT scanner can acquire a pair of anatomically contiguous slices at the rate of thirty-four (34) images per second. Compared with the rate of about one (1) slice per second for the third and fourth generation CT scanners, this acquisition time speed improvement is substantial. It represents a basis upon which a commercially viable CT scanning technology could be built. Admittedly current image reconstruction times and current automated image analysis times are still much slower than would be required of commercially useful systems. But as was mentioned above, future developments in microprocessor technology should help alleviate these two problems as well.

The computer vision system being developed at Virginia Tech for locating and identifying internal defects in hardwood logs using CT imagery can conceptually be divided into three components: a CT scanner-based data acquisition system, a low-level module for performing image segmentation, and a high-level module for recognizing the defects located by the low-level segmentation system. The capabilities of these various modules will be experimentally demonstrated.

II—Developing a CT Image Database

To develop any computer vision system requires a good deal of experimentation. The resulting vision system will be no better than the database of images used in its development. If the database of images is representative of the range of images the system will have to process in the real world environment, the system, once it is developed, will probably be effective in solving the problem it was intended to solve. If on the other hand the database of images used to create the system is not representative of the real world image data the computer vision system will have to handle, then the resulting system will probably not be able to perform its task effectively.

Because of the above, it is very important at the beginning of any computer vision development activity to spend a good deal of time preparing an appropriate image database. At the beginning of this research activity there was only one database of CT images of hardwood logs available. This database was the one created to perform the research work reported by [8]. This database was established by investigators at Mississippi State University in cooperation with the Southern Forest Experiment Station, U.S. Forest Service, and with the Imatron Corporation. This database consisted of a series of 256x256 by 8 millimeter contiguous slices of a red oak log section 12 feet long. This database, while containing a number of slices, is not very satisfactory for computer vision research for a number of important reasons. First and foremost was the way in which "ground truth" was established on this database. Whenever one is attempting to create an automatic method for analyzing images, he must be able to compare results obtained from the automatic analysis with the way the image should actually be interpreted, i.e., the ground truth interpretation. An image interpretation is the creation of distinct regions within the image and the assignment of labels to these regions.

To establish ground truth for a CT image slice of a log requires one to cut the log across the imaging plane used to create the slice and examine the log at the position of the cut to determine the location and extent of each defect. If a log has multiple contiguous image slices taken from it, establishing the ground truth for each of the slices becomes somewhat more complicated since the log must be accurately cut a number of times without any accumulative error build up. The problem is to make sure the surface of the log face visually inspected is accurately registered with the CT image associated with this surface.

The Mississippi State database was collected with the idea of being able to determine the ground truth for an entire log. The objective was to use this ground truth data to help determine the potential benefit of using internal defect locations to optimally position a log for cutup. As such, an entire log had to be scanned and the log had to be handled just as it came from the forest. Because of this there was only moderate registration between a log surface obtained from the cutup operation and the associated CT image slice obtained from Imatron.

Another problem with this data is that the ground truth information was in the form of hand digitized outlines. Hence, while one could compare the results of computer processing with the labeling assigned to these outlines, one could not get any feel for how serious any error might be. The final problem with this database is that it represents only one species, albeit a very important species, red oak.

To address these problems, a new CT image database was created for use in this research. The methodologies used to create this new database differed markedly from those used in creating the Mississippi State database. First, collecting CT imagery of logs, or for that matter anything else, is very expensive. Hence, it is very important that each slice provide as much information as possible. For the purposes of developing a computer vision system the "important information'' contained in each slice of CT imagery is the way different defects manifest themselves in relation to one another and to clear wood. Since the vast majority of any log is clear wood, the really important part of any CT image slice is that portion of the slice that represents an internal log defect. Hence, low grade logs were individually selected for use in creating the database. ,

The log diameters considered ranged from 10 to 16 inches. Each log was sawn so that it had one flat face. The reason for creating the flat face was so that the log could be positioned on the CT scanner. The objective was to create image slices perpendicular to plane defined by this flatface. From each log, one or more 15 to 28 inch sections were selected. The sections were selected based on an examination of log bark. The purpose of this examination was to determine the types of defects located internal to the section. The sections selected were cut from the logs. Obviously, each section also had one flat face, a face it inherited from the log from which it was cut. After each section had been cut from the log, a straight line cut was made down the length of the section, a cut that runs approximately down the middle of the section. This straight line cut was made onto the top of the section while the section was lying on its flat face. The straight line was used to position the section on the CT scanner so that the translation used to move the section into the scanner would be in the direction defined by the straight line cut. The flat face and the line cut were used so that good registration could be obtained between a cut made through a section and the associated CT image slice. All the above described processing was performed in a manner to prevent any drying of the log sections. The objective was to obtain images of "green" material.

To provide some information about the variations caused by interspecies differences in hardwoods, two species were selected for consideration, red oak, a high value ring-porous species, and yellow poplar, a low value diffuse-porous species.

The log sections were stored in cold-storage until they could be imaged on a CT scanner. The scanner used was one at a local hospital only a few minutes drive from the cold storage location. The CT scanner used was a Seimans Somaton DR2 system. Slice spatial resolution was 2.5x2.5 millimeter within slice plane and 8 millimeter thickness. Each slice represented a 256x256 image with 16 bits of CT number information. Once scanned the images were stored on 10 inch floppy disks machine readable by Digital Equipment PDP-11 computers running the RT-11 operating system. The images on these double density disks were transferred to a VAX 11/785 computer for processing. All the CT images were then stored on computer tape. Several tape backup copies were made to assure that the CT image data base would not be lost.

After the sections were scanned they were returned to cold storage. Within a very few days each section was removed from cold storage and was cutup using a Woodmizer saw into very thin slice sections that corresponded as closely as was possible to the CT image slices taken by the Seimans scanner. Each thin section slice was labeled, washed, bagged with the other thin slices cut from the same section, and returned to cold storage. The goal was to perform all this additional processing without drying out the thin wood sections.

The last step involved in creating the CT image database was to take a color photograph of each thin wood slice. Appearing in each photograph is information that allows one to determine the CT slice number for which this thin wood slice is supposed to correspond, the log section from which the thin slice was cut, the log from which this log section was cut, and the species of this log. The film negative and the 5x7 color print of each thin wood slice have all been saved for archival purposes.

A total of 490 CT image slices, color photographs, and film negatives comprise this image database.

III—3-D Segmentation by Volume Growing

The original 12-bit CT images of hardwood logs contain several types of picture elements (pixels), such as air (background), clear wood, knots, splits, bark, and so on. Besides, there is a textural structure on each of the CT log images that represents the annual ring structure of the tree growth. These fine rings are visible both in the sapwood and heartwood, and they tend to grow in the same textural pattern or directionality. To effectively distinguish defects from clearwood and air, we find it necessary to eliminate these annual rings before segmenting an image into a number of uniform regions.

One of the major characteristics of the annual rings is their high frequency property. This is so because a typical tree will grow one annual ring each year and the distribution of these annual rings is much denser compared with the grain patterns of other components of the log. In the signal frequency domain, they manifest themselves as a high frequency component of the digital image signal. In general, to eliminate high frequency component from a digital image, the linear or nonlinear lowpass filters are adopted to smooth the image. These filters are composed of a set of coefficients that can be computed or updated according to their input image signal. Depending on the dimensions of the input digital image, the filter can be 2-dimensional or 3-dimensional. If the filter is 2-dimensional, it operates on the image data in a square window of a certain size. If it is 3-dimensional, it operates on the data in a cubic window.

Our goal in image smoothing is to eliminate the annual ring structure while preserving defects on the image. For this purpose, a nonlinear adaptive filter was used that is particularly efficient. It adaptively cornputes a linear combination between a noisy image and a restored version of this noisy image obtained by an initial filtering. The purpose of this procedure is to improve image restoration performance by using a rather simple structure. In contrast with previous work, this approach is based on a filter of fixed structure rather than on simplified assumptions about the image signal model. Simulation and experiment examples indicate that it is capable of reducing noise efficiently while preserving image details. This is especially attractive to our image smoothing problem since it can smooth out the annual ring structure while preserving the fine splits and checks.

As in most cases, the observed image signal at an image pixel consists of two uncorrelated components: true signal and corrupting noise. Filtering or smoothing is adopted to improve the signal-to-noise ratio at most points of the image. However, in regions of heavy edges or texture, filtering may degrade the image more than it actually reduces noise. In this case, a compromise would be not to do any filtering on the data (such as splits). On the other hand, for non-textured or non-edged areas (such as clearwood), we may want to filter them using the filtering operation. Accordingly, to obtain an optimal estimate of the true image signal at point, a weighted sum of the noisy signal and its filtered version is constructed at an estimate of the true image signal. The coefficients of the filter are the parameters that need to be computed from the image data.

These filter coefficients are adjusted so that: (1) for edged regions (such as splits), the noisy observation is kept by down weighting the restored signal; and (2) for non-edged regions (such as clear wood), the initially restored signal is kept by down weighting the noisy observation. It is noted that the pixel value at a point on the kth slice is closely correlated with those at its neighboring points on the (k - 1)th and (k + l)th slices in a sequence. Hence one way of improving the filtering performance is finding the optimal solution for a least squares (LS) problem defined in a 3-dimensional volume. By solving this 3-dimensional problem, filter coefficients can be computed from the image data in consecutive slices in a sequence. The typical values for the filter window size are from 1 to 3 pixels, depending on input images. To calculate the optimum filter coefficients a LS criterion is introduced to minimize a quadratic error index. With the filter coefficients so computed, the original 12-bit image is filtered on a pixel-by-pixel basis. The output from the filter is a filtered image which is to be segmented by a procedure described next.

Images that have first been filtered using the above filter are thresholded on an image-by- image basis using a multi-thresholding method. A histogram *h(k)* is computed first from the filtered image data and smoothed with a Gaussian function, resulting in a smoother histogram on which the thresholding operation is based. An ordinary CT log image consists of pixels representing background, decays, splits, knots, barks, and clear wood. Accordingly, three thresholds $\{T_1,T_2,T_3\}$ are determined from the histogram *h(k)*. They are used to divide each image slice into a number of uniform regions. These three thresholds $\{T_1,T_2,T_3\}$ are determined according to the following criteria:

1. T_1: $T_0 £ T_1 £ T2-d$, where T_0 and d are adjustable constants.

2. T_2: the location of the maximum of $h(k)_{<}$, the second derivative of *h(k)*.

3. T_3: the location of the first zero-crossing of $h(k)_{e}$, the first derivative of *h(k)*.

Image grey level thresholding using the above three thresholds, $\{T_1,T_2,T_3\}$, produces a number of regions that represent potential defects, as well as a small number of spurious defect regions of different sizes. In order to facilitate the later processing steps and to improve defect recognition accuracies of the vision system, this later category of regions needs to be eliminated before region detection. For this purpose, morphological operations such as erosion and dilation defined by morphological masks are applied to the segmented image. The morphological operations are applied to the CT images to eliminate spurious regions and to smooth defects. In our vision system, an image erosion operation is first performed on the segmented image to get rid of small spurious areas. Then an image dilation is performed to restore those pixels of the real defect regions that have been eliminated by the erosion operation.

The above segmentation-filtering process produces a number of uniform regions on each image which, when grouped together in 3-d, represent the 3-d information of different wood defects inside a log. A 3-d version of the connected component labeling algorithm [7], called *3-d volume growing,* is adopted here to segment or group individual 2-dimensional regions on different slices into 3-d integral objects.

Inside a log, defects manifest themselves in varying shapes. In 3-d, a knot would appear like a paraboloid, bark like a generalized cylinder, a hole like a cylinder, and a split like a ribbon, etc. To identify the proper 3-d volumes of potential defects, pixels with similar CT attributes on a number of segmented images are grouped into connected volumes, according to 6- or 18-neighborhood connectiveness in 3-d.

The above segmentation approach can also perform quantitative estimation of structures of a 3-dimensional object, and this volumetric information can be used in recognizing unknown structure in a scene. This estimation can be achieved by counting the number of pixels that have the same label assigned by a 3-dimensional volume growing algorithm modified from [71. An integer value is preset as a threshold for volume size against which all the labeled volumes are to be compared. Any volume of a size smaller than this threshold value is eliminated by merging it with its nearest neighboring volume or merging it with the background. This merging process usually eliminates false defects resulted from segmentation, and retains the well-connected 3-dimensional objects as defects, such as knots, bark, splits, decays and holes. Output from this 3-dimensional volume growing algorithm is a number of 3-dimensional objects that are to be recognized by the high-level module discussed in the next section.

IV—Defect Recognition-A Rule-based Approach

Any defect type may manifest itself in many different ways. For example, knots represent a single type of defect; however, their shape, density, size, and orientation can vary greatly. Consequently, statistical or analytical classification procedures are difficult to implement successfully. Less exacting methods, therefore, may be better suited to this type of problem. A heuristic, rule-based recognition system was used by [3] to identify defects in sawn lumber. Rule-based systems are flexible in that special rules can be written to handle exceptions [1]. For these reasons, the machine vision system under study adopts a rule-based approach to perform 3-d object recognition.

For each of the 3-d *volumes* detected by the above volume growing process, statistical, geometric, and topological features are readily computed from the 3-d image data. Currently, 5 basic features have been derived to enhance the separability of bark, knots, and clear wood. Additional features will be added to the system as other defects need to be recognized or as current defects need to be distinguished better. The following are brief descriptions of the object features that may be computed from a sequence of images:

(1) *The mean value (MEAN)*— This feature is obtained by finding the mean CT values for all pixels contained in a volume. Because knots have higher absorption rates than clear wood, this is an important feature to identify defects.

(2) *The variance value (VAR)*— Sample

variance of a volume is calculated as in the calculation of MEAN above. This is a useful feature to distinguish bark from knots because they have different variance values.

(3) *The minimum distance (DIST)*— This is taken as the distance from the centroid of a *volume* to the Z-axis. Bark (except for included bark pocket) is a great distance away from the center (Z- axis) of the log, therefore, it has a large DIST value. Clear wood is near the center of the log, and it has a small DIST. Therefore, this is a good feature to identify bark.

(4) *The predictor (TOUCH)*— This is a binary predictor with value 1 or 0. Valuel (O) indicates a *volume* touching (not touching) the background (air). Since knots usually do not touch air, this is a good feature to differentiate knots from other objects.

(5) *The Volume (VOLM)*— This is the 3-d volume occupied by an object. Clear wood has a much larger volume than any other objects in a log. Splits and holes usually have a small volume. Therefore, this is a good feature to distinguish clear wood from defects, and splits and holes from the remaining defects.

Each object has a confidence vector to describe the belief that the object belongs to each defect category. From the population distribution of a given feature, we can derive threshold values that separate the population of values for that feature into discrete classes. To properly define ranges on the feature distributions for different linguistic qualifiers, a group of threshold values are determined using a set of training data. Threshold values are visually determined by the peaks and valleys on the histograms of individual features. Linguistic qualifiers, such as "high" and "low", label these classes. An *evidence function, expressed* as a discrete or continuous step-type function, can be used to relate linguistic qualifiers and levels of evidence for various defects. Fig. 1 shows three examples of such *evidence functions f(v)* for feature *v = VAR* for the defects bark, knots, and clear wood. According to these step-type functions, a linguistic qualifier L (for Low), M (for Medium), or H (for High) is associated with ranges of values of the feature variable v. Here Tl and T2 are two thresholding values obtained from a histogram of the feature v. For each feature value computed from image data, such functions assign individual values to the confidence vector for a candidate *volume.* This is in fact a voting process where a higher vote is given to the strong evidence and a lower vote to the weak one.

To use prior knowledge about different categories of defects to classify a candidate object, a correspondence must be established between the linguistic qualifiers and possible defect manifestations within a log. A production system or rule-based approach is adopted since it easily implements this type of reasoning. There are many ways to combine feature values and decision paradigms to make rules. Antecedent conditioning could refer to the value of a single feature, the values of all the features, or the values of some subset of the features. The consequent action could make a decision on membership or non-membership in a class, or simply contribute evidence to that decision.

In our approach, a production system with simple conditions was built; each rule considers one basic feature. The action of a rule is to contribute positive evidence (1.0) to classes in which the feature is usually present, negative evidence (-1.0) to those in which it is usually absent, and no evidence (0.0) to the rest. To accommodate situations where the feature is present occasionally and absent at other times, half evidence (0.5 or -0.5) is contributed to the classes. The rules in a production system are of the following form

IF (conditions) THEN (actions).

In implementing rules, individual rules are grouped into conjunctive rules, where the action part contains several confidence value assignments. As an example, the conjunctive rule *Rule-Touch* using feature *TOUCH* is expressed as

Rule-Touch : vote to 3 classes by feature TOUCH

if(touch(k)=l) then ("touching")

cv(touch, bark) = 1.0

cv(touch, knot) = -0.5

cv(touch, wood)= 0.5

elseif(touch(k)=0) then ("not touching")

cv(touch, bark) = 0.5

cv(touch, knot) = 1.0

cv(touch, wood) = -0.5

In this rule, variable touch(k) is the TOUCH feature value of the kth *volume,* and cv(touch, bark), cv(touch, knot), and cv(touch, wood) represent the confidence values assigned by rule *Rule-Touch* to bark, knots, and clear wood respectively. This rule provides strong positive evidence (1.0) for bark that touches the background, whereas it provides weak negative evidence (-0.5) against a knot that touches the background.

After applying all 5 rules to a candidate *volume*, a matrix of confidence values cv(i,j), (i = 1,2,...,5, j = 1,2, 3.) are generated. The *total vote* for an object, denoted by *TV(j),* is the total confidence value obtained by adding up all the confidence values assigned to the object by all 5 rules. For an expert system comprised of *N,* rules, this *total vote* can be expressed as

$$TV(j) = \sum_{i=1}^{N_r} cv(i,j),$$

In our case, N_r, the number of rules, is equal to 5. The class with the highest total vote is designated as the class to which the object belongs. The next section shows some experimental results of applying these rules to CT images taken from a hardwood log.

V—Experimental Results

The method described in this report was applied to recognize CT images taken from red oak and yellow poplar logs that contained bark, knots, and clear wood. The original 12-bit images were 256 x 256 with pixel resolutions 8.0mm between slices and 2.5mm within a slice. After 3-d smoothing, images were segmented one by one, and the connected components on all slices were grouped together to produce a number of 3-d *volumes* of unknown defect type.

Experiments were conducted using the above described approaches to process CT images and to recognize wood defects from several red oak and yellow poplar logs. Fig. 2 shows an original red oak CT slice, its histogram, and segmented images without filtering and with filtering. It is noted that a thin split and two knots, as well as bark, are picked up by the vision system. Fig. 3 demonstrates the results of image filtering and segmentation with 2 different samples of red oak. On the upper part of the picture, one can observe the bark, a brown decay, a split, 2 knots, as well as the clear wood area. On the lower part, there are the bark, a large brown decay with darker splits, and several decolorized clusters. Fig. 4 contains a sequence of 4 original CT slices, and Fig. 5 is the result of performing 3-d volume growing operation on them. It is clearly seen that the system has picked up several potential defects from these 4 images.

In the defect recognition experiment, a small set of CT slices were selected from a sequence of the log images as the training data. Feature distributions computed from this training set defined a set of thresholding values that were used to determine the linguistic qualifiers of the feature values. Rules were then applied to individual candidate *volumes* to assign confidence values to different defect classes. Adding up the confidence values contributed to a *volume* by all rules, the object was assigned the class that had the highest total confidence value. In the paper, recognition results from one of these experiments with a yellow poplar log are illustrated. Fig. 6 presents the original CT images of 4 slices which contain bark, knots, and clear wood. Fig. 7 contains the results of applying the above mentioned defect recognition method to this sequence of segmented images. On reviewing Fig. 6 and Fig. 7, it is obvious that two pieces of bark (marked as bl and b2) and one knot (marked as kl) have been detected, and that the clear wood and the background (air) are also correctly differentiated from the defects.

VI—Concluding Remarks

In this paper we have presented a computer vision system that is designed to inspect hardwood logs using CT imaging. The main advantage of this vision system approach to log inspection is that it is possible to locate, and identify defects inside a log. Our aim is to demonstrate usefulness of this approach. As an example, we have taken CT log images and shown some defect recognition results. Clearly, CT image sequence analysis is a complicated problem in practice. Therefore, the approach presented in this paper needs to be improved in order to accommodate more complicated log defects and to make the system more robust. Furthermore, to more precisely identify each defect that has

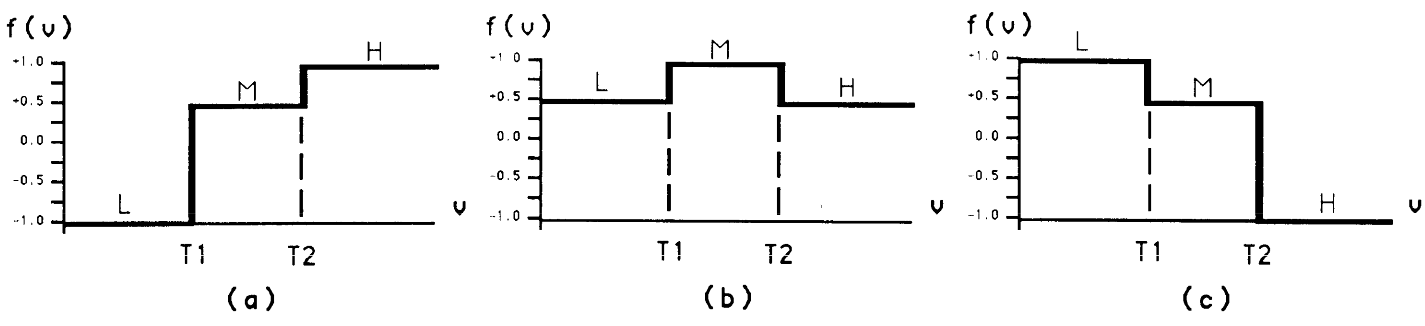

Fig. 1 An evidence function *f(v)* relates discretized values (L, M, H) for feature $v = VAR$ with evidence values for the defect bark (a). Knots (b) and clear wood (c) have different evidence functions. The threshold values, T1 and T2, were established from the distribution of *VAR* values.

been detected, more work is needed to efficiently calculate other measures rather than the volume, such as the orientation and minimum bounding volume. Nevertheless, the proposed approach to wood inspeciton seems to indicate that a relatively simple and efficient vision system for hardwood log inspection can be developed.

References

[1] S. Bartlett, C. Cole, and R. Jain, "Automatic solder joint inspection, *IEEE Transactions on Pattern Analy-sis and Machine Intelligence*, vol. PAMI-10, no. 1, pp. 31-44, Jan. 1988.

[2] Sun Joseph Chang, "Economic feasibility analysis of fast NMR imaging scanner," *Proc. 3rd International Conference on Scanning Technology in Sawmilling*, San Francisco, CA, Oct. 1989.

[3] T-H Cho, R. Conners and P. Araman, "A computer vision system for automated grading of rough hardwood lumber using a knowledge-based approach," *Proc. 1990 IEEE International Conference on Sys-*

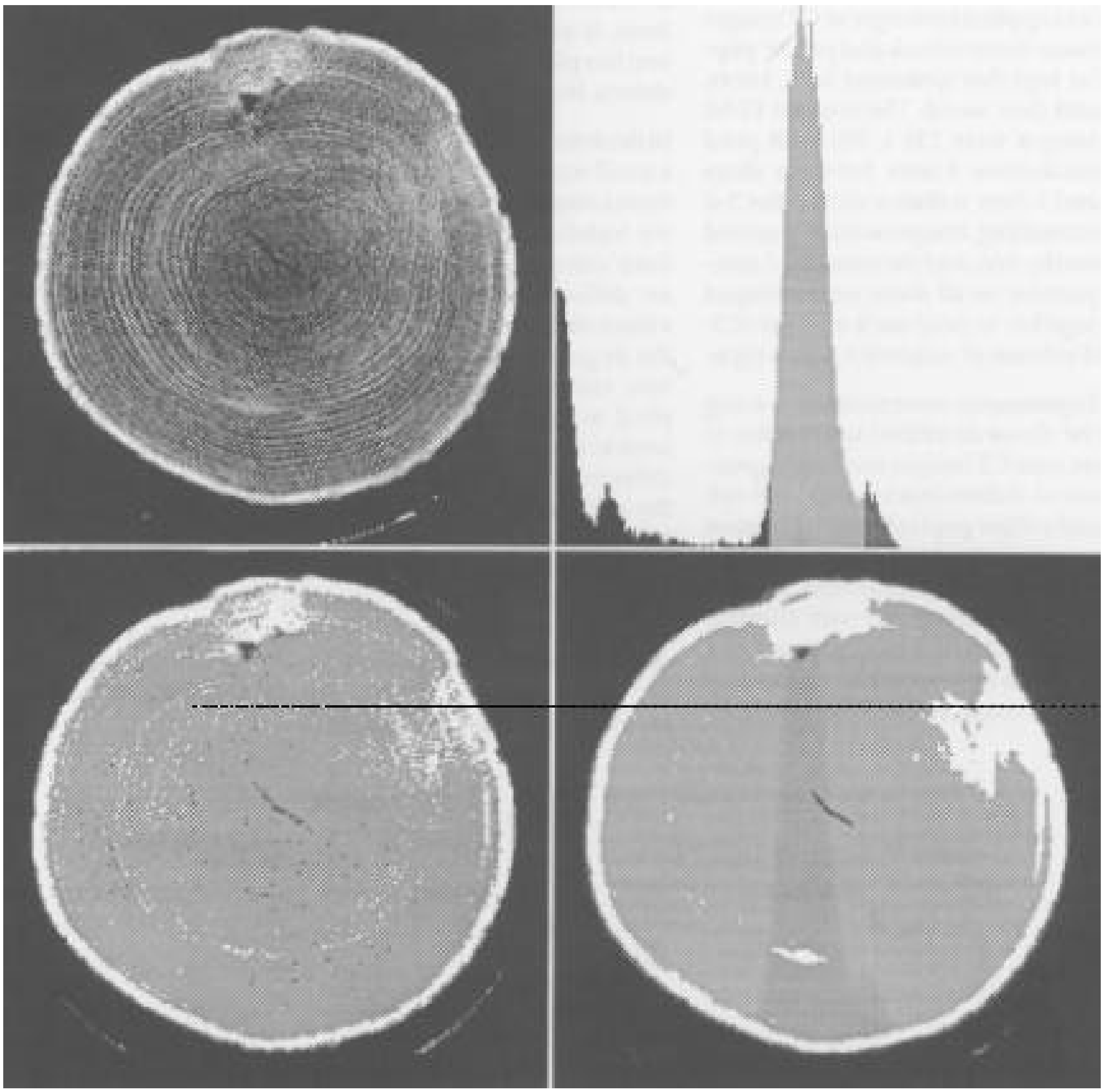

Fig. 2 From upper left clockwise: (a) a red oak CT slice, (b) its graylevel histogram, (c) segmentation without filtering, (d) and segmentation after filtering.

tems, Man, and Cybernetics, Los Angeles, CA, November 1990.

[4] B. V. Funt and E. C. Bryant, "A computer vision system that analyzes CT-scans of sawlogs, *Proc. of IEEE Conference on Computer Vision and Pattern Recognition*, pp-175-177, 1985.

[5] F. Taylor, F. Wagner, C. McMillin, I. Morgan and F. Hopkins, "Locating knots by industrial tomography—a feasibility study," *Forest Products Journal*, vol. 35, pp. 42-46, 1983.

[6] D. B. Richards, "Value yield from simulated hardwood log sawing," *Forest Products Journal*, vol. 27, pp. 47-50, 1977.

[7] Y. Shirai, *Three-Dimensional Computer Vision*, Springer-Verlag, New York, 1987.

[8] F. Wagner, F. Taylor, D. Ladd, C. McMillin and F. Roder, "Ultrafast CT scanning of an oak log for internal defects," *Forest Products Journal*, vol. 39, pp. 62-64, 1989.

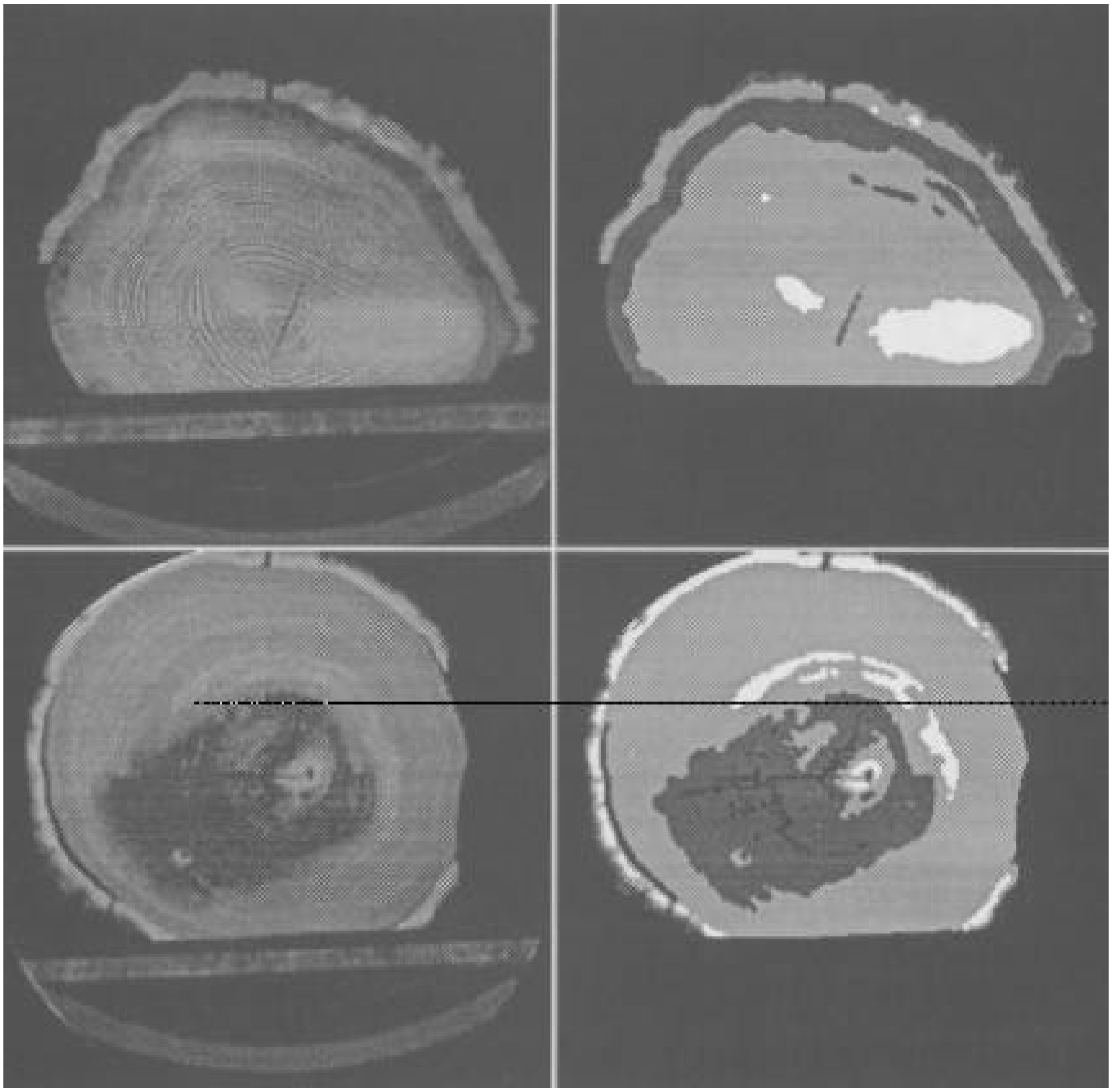

Fig. 3 Upper: original and segmented images of a red oak slice RK11.22; Lower: images from a different red oak sample Rk12.05.

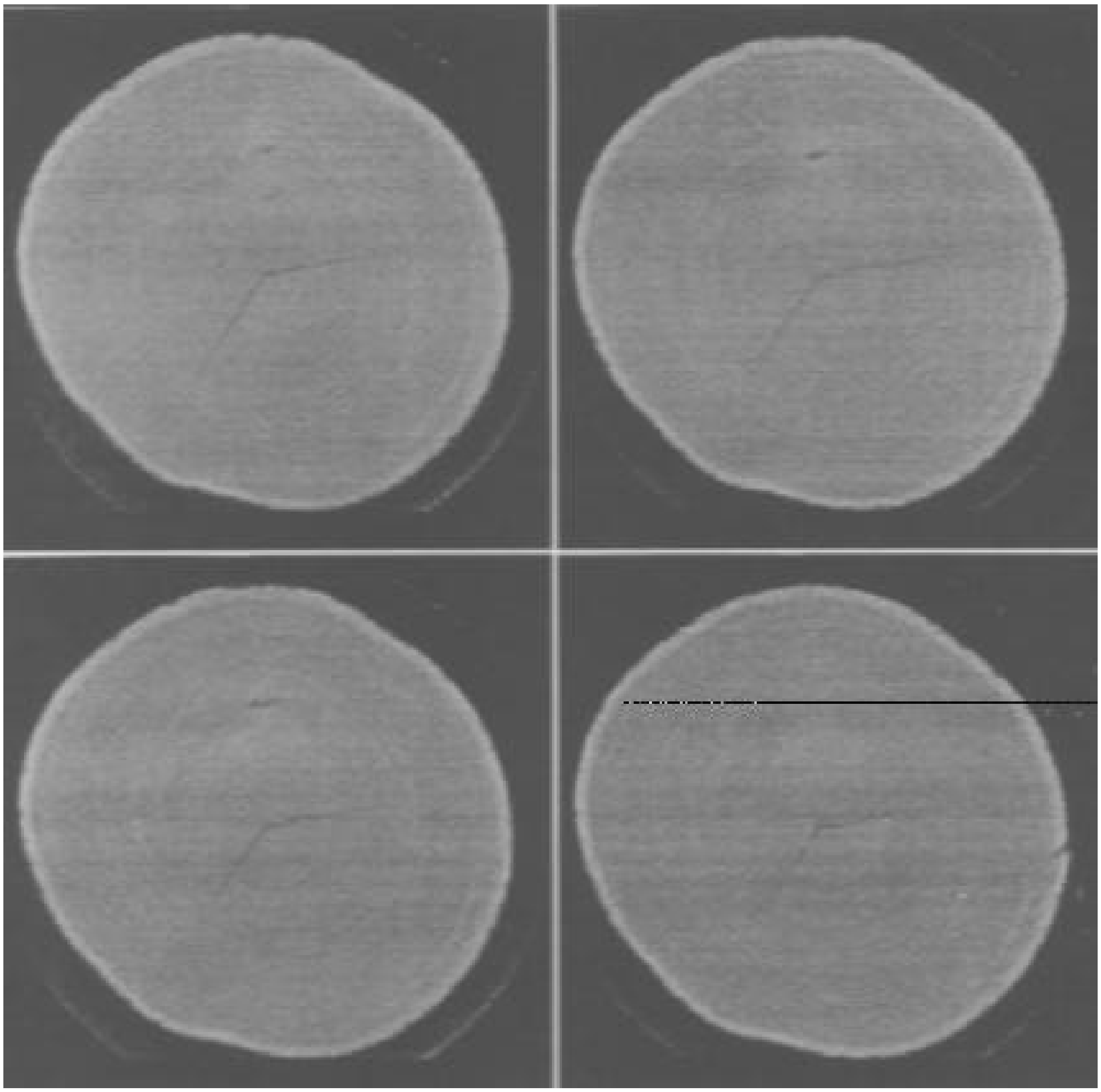

Fig. 4 From upper left clockwise: 4 consecutive images from a red oak log (Log4.S4 to S9).

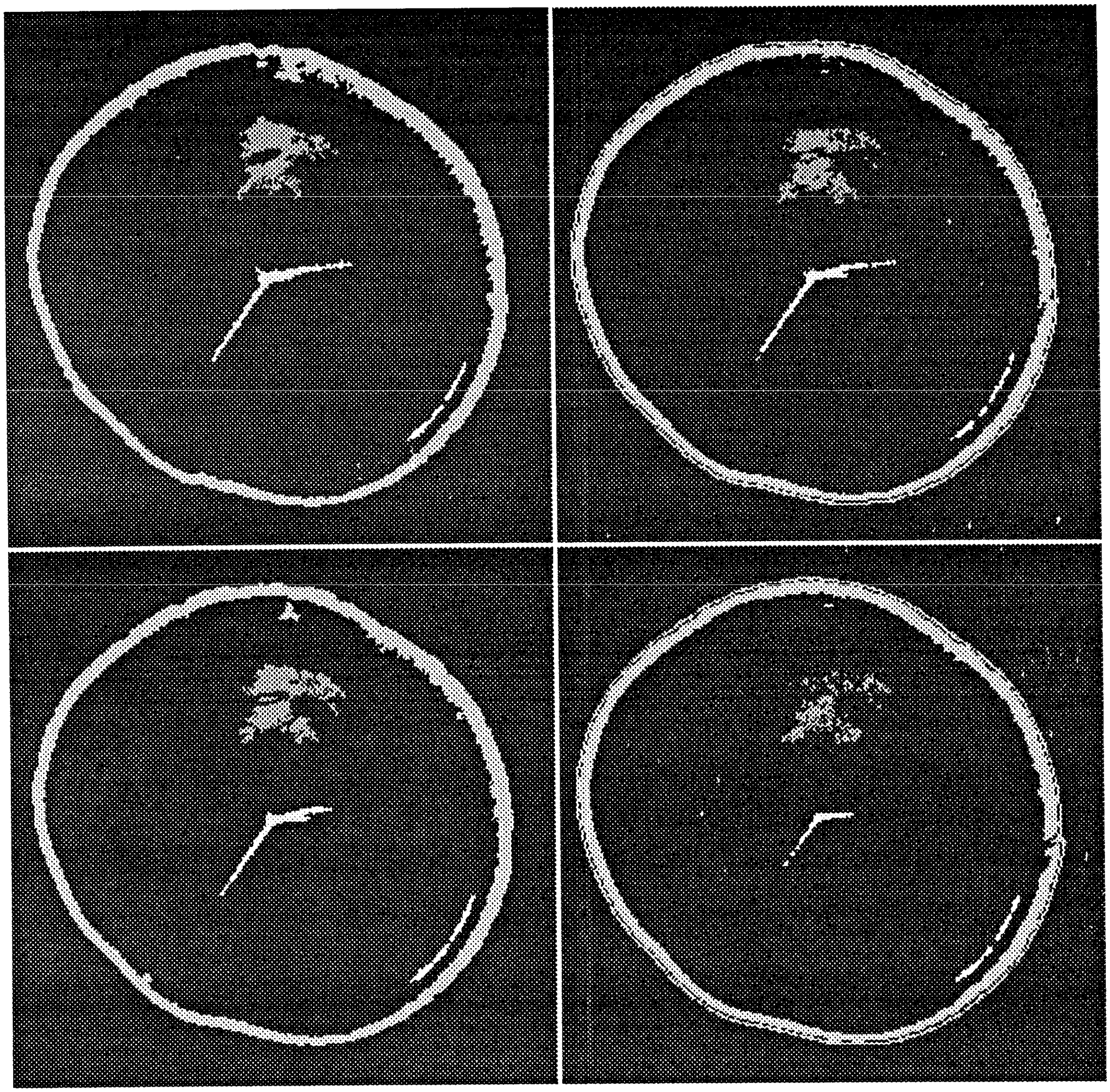

Fig. 5 From upper left clockwise: 3-dvolume growing results of the 4 images in Fig. 4.

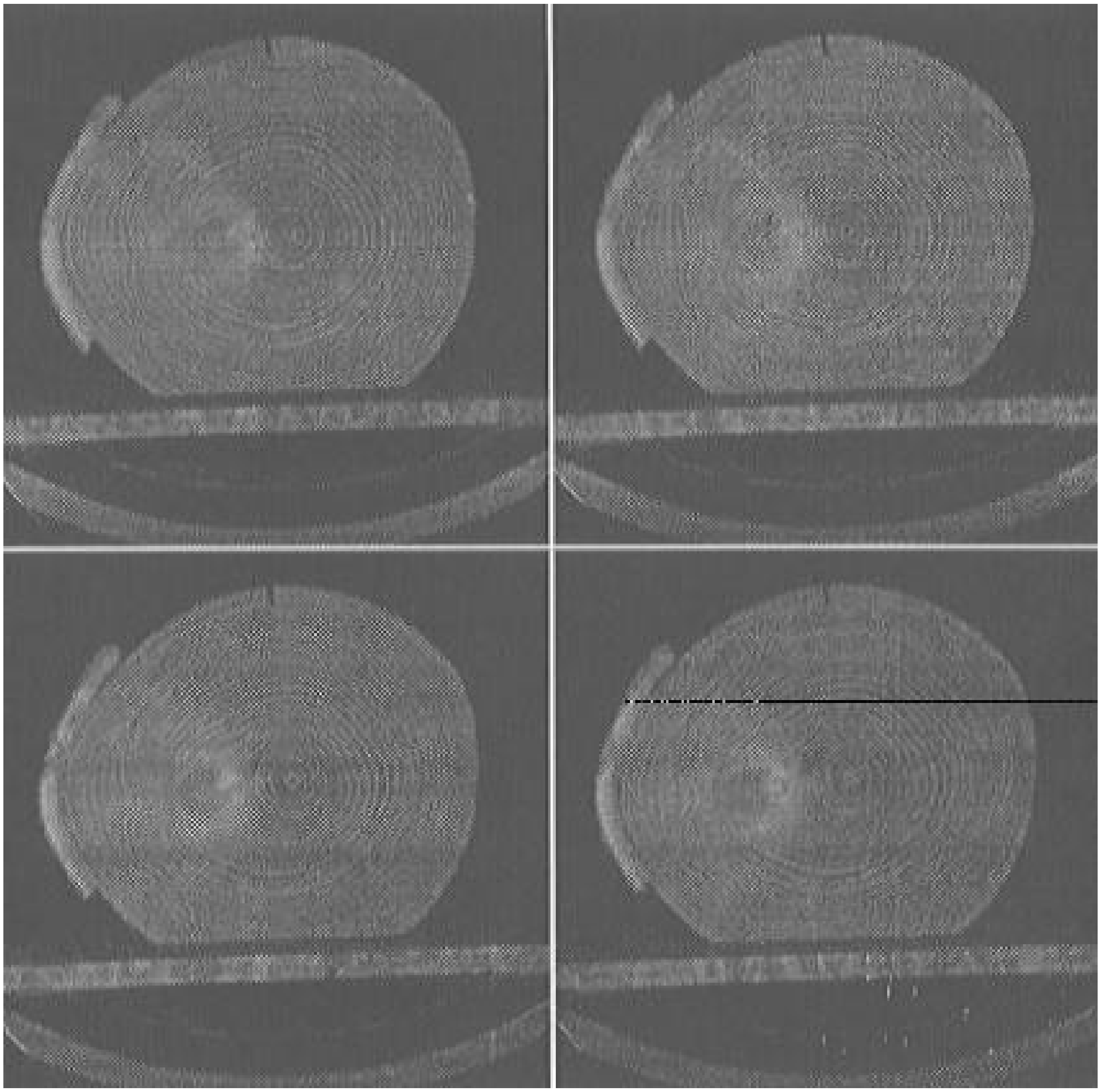

Fig. 6 From upper left clockwise: 4 consecutive images from a yellow poplar log (yp01.02 to 05).

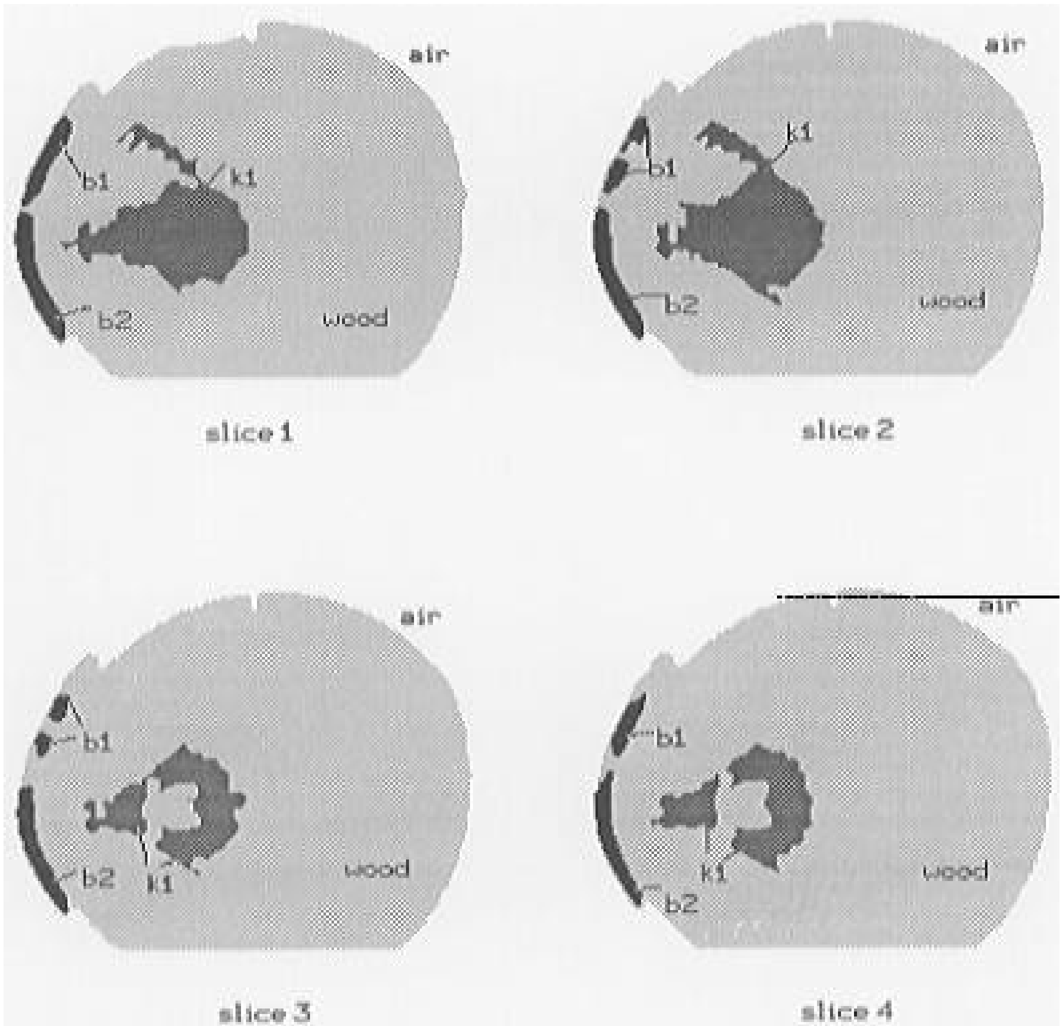

Fig. 7 From upper left clockwise: recognition results of the 4 images in Fig. 6. (The two pieces of bark are marked as b1 and b2, and a knot as k1.).

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