A System for Detection of Internal Log Defects by Computer Analysis of Axial CT Images

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Abstract

This paper presents a system for detection of some important internal log defects via analysis of axial CT images. Two major procedures are used: the first is the segmentation of a single computer tomography (CT) image slice which extracts defect-like regions from the image slice, the second is correlation analysis of the defect-like regions across CT image slices. The segmentation algorithm for a single CT image is basically a complex form of multiple thresholding that exploits both the prior knowledge of wood structure and gray value characteristics of the image. The defect-like region extraction algorithm first locates the pith, groups the pixels in the segmented image on the basis of their connectivity and classifies each region as either a defect-like region or a defect-free region using shape, orientation and morphological features. Each defect-like region is classified as a defect or non-defect via correlation analysis across corresponding defect-like regions in neighboring CT image slices.

1. Introduction

Production of lumber is essentially a breakdown process. With each cut into the log, new information is divulged on the quality of the wood inside which often suggests a different and better cutting pattern. Since each step in the cutting process is irreversible, the loss in the value yield has already happened. A detailed knowledge of the presence, location, and size of internal defects prior to the first cut into the log may lead to potential gains of about 15 to 18 percent in lumber value [5] [7]. On a national basis this represents a savings of $2 billion for the hardwood lumber industry.

Studies of computer tomography (CT) and nuclear magnetic resonance (NMR) scanning for internal log defects [1] [2] [3] [6] [7] have demonstrated that both CT and NMR scanners available today can be used successfully to image the internal features of logs. CT scanners which are essentially solid state (no moving parts) can scan at rates exceeding 30 slices per second. Thus the technical feasibility of scanning logs in real time is approaching reality. However, the methods for interpreting the CT scans of logs reliably are not clearly understood yet.

In this paper, we present a system for detection of knots and cracks, two important defects that affect lumber value, via analysis of a set of cross-sectional CT images. The images were captured using a Toshiba TCT 20AX CT scanner for three representative hardwood species -- Red Oak, *Quercus spp.* (ring porous); Black Walnut, *Juglan nigra.* (semi-ring porous); and Hard Maple, *Acer spp.* (diffuse porous). The system adopts a bottom-up design approach, that is, it first processes each single image, and then relates the processed results of each CT image across neighboring CT images to extract defects. Figure 1 depicts the flowchart of the system.

2. Segmentation of a single log CT image

A CT image of a log cross-section is generally composed of four groups of gray-level intensity values. From the lowest to the highest gray-level value they correspond to pixels from (1) air (i.e. cracks and large voids), a few parts of rot, and parts of earlywood; (2) rot, earlywood, and a few parts of latewood; (3) latewood and a few parts of knots; (4) knots and some parts of latewood (see Figure 2). Thus a multiple thresholding algorithm is suitable for segmenting the CT image into four classes.

2.1 Area-based multiple threshold selection

The gray level histogram of the CT image has a multi-modal shape. It is difficult to select multiple thresholds using the standard threshold selection method [4], even though a smoothing technique is applied to

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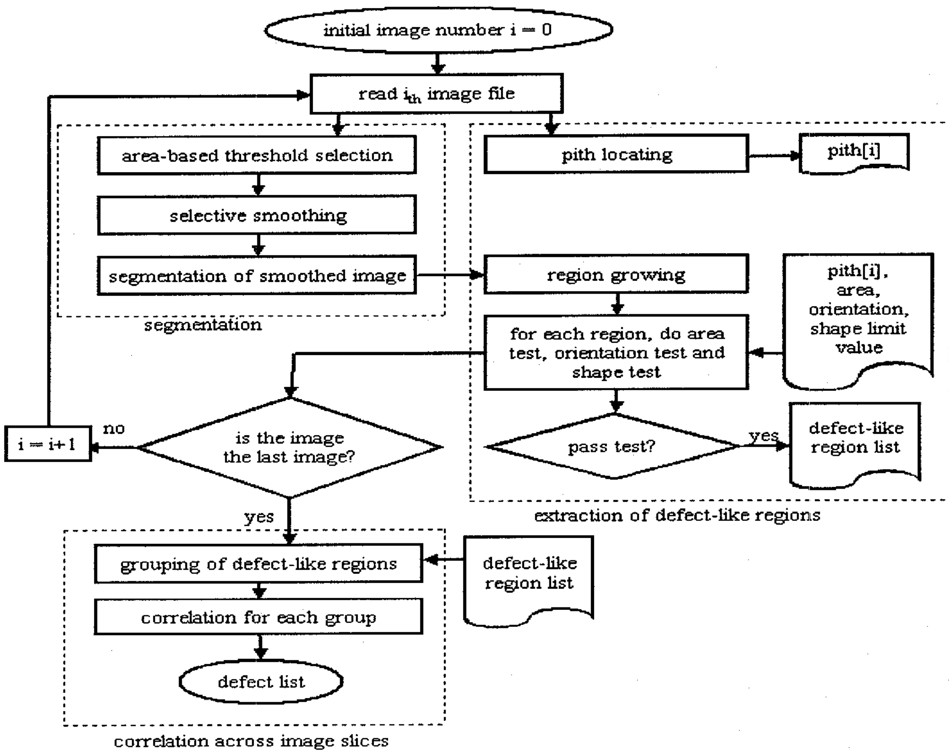

Figure 1. Flowchart of the system

suppress trivial peaks in the histogram. This is because (1) there are too many peaks in the histogram which can not be suppressed by the histogram smoothing technique and (2) the valleys between histogram peaks are long and flat making threshold selection difficult. We solve this problem by using a very simple threshold selection technique which we term as *Area-based Multiple Threshold Selection.* This technique incorporates the heuristic that the image does not contain a single large region whose pixel gray-level values lie within a narrow range if the annual rings of wood are not broken and that the earlywood and latewood constitute a major portion of the image. The heuristic method works as follows (Figure 3):

1. Suppose the pixel group with the lowest gray-level range (or the first class) and the pixel group with the highest gray-level range (or the fourth class) account for p1 and p2 percent of pixels in the log CT image, respectively. As long as p1 and p2 are sufficiently large, cracks and knots are assured to be included in the first and fourth class respectively. On the other hand, the fact that the gray level of earlywood (or cracks) is significantly lower than that of knots (or latewood) prevents the growing of a large connected region that contains both a crack and a knot. Also, the risk of adding false cracks and knots is small if p1 and p2 are not too large. Generally p1 is 3-5% and p2 about 10-15%.
2. Assign the first threshold as g1, where
$$\sum_{0\le i\le g1} histogram[i] = p1$$
and the third threshold as g3, where
$$\sum_{i\ge g3} histogram[i] = p2$$
Here *histogram[i]* is the relative frequency of gray level *i*. The second threshold g2 is chosen such that
$$\sum_{g1<i\le g2} histogram[i] = (100 - p1 - p2)/2$$

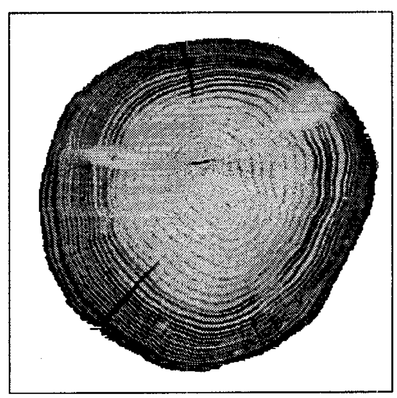

Figure 2. A raw CT image of Red Oak.

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2.2. Selective smoothing of the CT image

The CT image of a log contains a fair number of gray-level transitions among early wood, latewood, and knots. However, since each CT scanner's spatial resolution is limited (ours is 0.75mm by 0.75mm), a single pixel in the CT image may actually include wood elements from two or more classes but may only be assigned a gray level corresponding to a single class. Sometimes a small portion of wood may have abnormal density or may be assigned an incorrect gray value by the scanner (these pixels are termed as noisy pixels). If the thresholds selected above are directly applied to the raw CT image, one may experience the problem of oversegmentation and/or undersegmentation. In an oversegmented image a connected group of pixels arising from a single wood structure may be split into more than one region. In an undersegmented image pixels belonging to distinct wood elements may be incorrectly merged into a single region. This could result in misclassification of normal pixels as defects and also failure to detect certain defects. It is therefore necessary to smooth the CT image to avoid problems of under/oversegmentation. Our selective smoothing algorithm designed for this purpose can be described as follows (Figure 3):

1. Suppose the pixel percentages for each transition are known. From these percentages and the gray-level histogram, both the lower gray level (g_{low}) and the upper gray level (g_{up}) of each transition are computed.
2. For each pixel with gray level between g_{low} and g_{up}, modify its gray level by applying a majority filter: if the number of pixels in its 8-neighborhood with gray level between g_{low} and g_{up} is greater than or equal to 5, then keep its gray level unchanged, else if the number of pixels in its 8-neighborhood with gray level less than g_{low} is greater than or equal to the number of pixels in its 8-neighborhood with gray level greater than g_{up}, set its gray level to a value lower than g_{low}, or else set its gray level to a value greater than g_{up}.

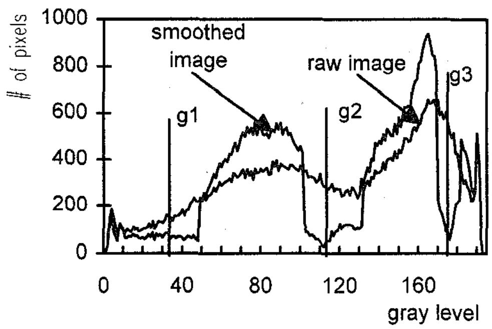


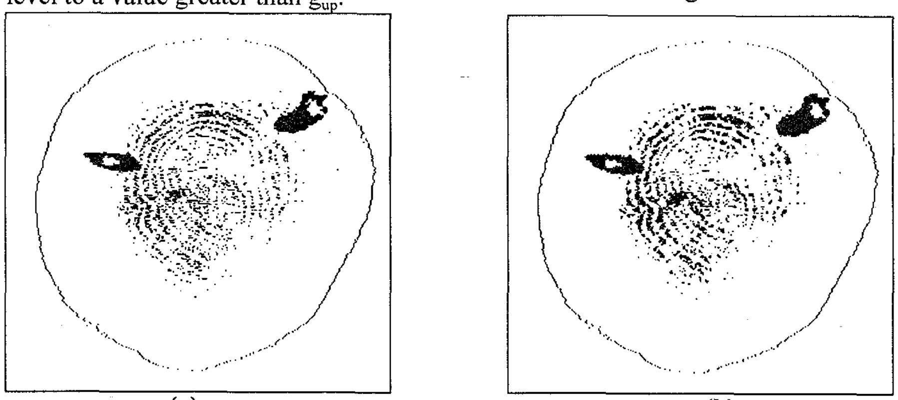
Figure 3. Histogram of the image and threshold selection.

Figure 4 shows the difference between the segmentation results of the original image and the smoothed image. The knot-like region in the upper-right corner of the smoothed image has a hole bounded by a closed contour but not so in the raw image. A small knot near the center of the image can be detected in the smoothed image but probably not in the raw image.

Since the gray value of sapwood is significantly lower than that of heartwood for some wood species, the above selective smoothing technique is not always effective for transitions between earlywood and latewood. In this case different g_{low} and g_{up} values for earlywood-latewood transitions of sapwood and heartwood may be necessary. But for the purpose of detecting knots and cracks, the aforementioned smoothing algorithm works well.

3. Extraction of defect-like regions from a segmented CT image

After the three thresholds determined in section 2.1 are applied to the smoothed image, the image is segmented into 4 classes. We ignore the second and third classes



(a) (b)

Figure 4. Pixels from the fourth class: (a) in the raw image (b) in the smoothed image.

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because they are mostly comprised of earlywood and latewood. The pixels from the first class and the fourth class in the smoothed image may correspond to cracks and knots respectively (Figures 4b and 5).

3.1 Locating the pith

The physical pith is a small area and may be viewed as the biological center of a tree although it is rarely located in the geometric center of the log cross-sections. It has an important role in aiding the identification of various wood features, for example, growth rings form a circular pattern with the pith at the center, and the longitudinal axes of knots and cracks normally pass through the pith.

Assuming that the pith is the innermost portion of the growth rings and that the growth rings are nearly circular in shape, an algorithm for locating the pith using the Hough transform for circle detection is as follows. First, apply the Sobel edge operator on the raw image and get an edge direction image using an edge strength threshold. Then, for each edge point in the edge direction image, calculate the centers of sets of circles within a certain radius range and passing through the edge point and increase the elements of the Hough accumulator array corresponding to the locations of the centers by unity. Finally the location in the accumulator array with maximum value is selected as the location of the pith.

We found that preprocessing of the raw image prior to using the Sobel operator, using the Laplace-of-Gaussian operator which produces a binary image, is useful for improving the pith location precision and facilitates the choice of the edge strength threshold. In addition, just a portion (about 1/3 of the log cross-section area) of the image near its center needs to be processed since the pith rarely lies near the boundary of log cross-section. Table 1 summarizes the results of the pith locating procedure.

3.2 Identification of defect-like regions

Pixels in the image belonging to the first class are grouped into the same region if they are 8-connected (i.e. indirect neighbors or direct neighbors), whereas 4-connected pixels (direct neighbors) belonging to the fourth class are placed in the same region. For each region obtained from the region growing process, an area criteria was first used to decide whether it should be retained for further processing or deleted from the region list. If a region passes this area test, the orientations of its major and minor axes are computed. Since the knots and cracks are generally characterized by a major axis passing approximately through the pith whereas the regions comprising the annual ring structure of the wood are not, the knot-like or crack-like regions are easily detected by an orientation test. A typical result of this step is shown in Figure 6.

Table 1. Results of the pith locating procedure

species	# of images	% of images with pith location precision within		
		5 pixels	10 pixels	20 pixels
Maple	696	54.5	77.3	99.0
Oak	770	60.5	83.0	98.9
Walnut	455	83.2	97.8	100

A region retained in the list often has some spike-like branches which are deleted using a raster-scan algorithm. The region's morphological features such as slenderness (measured as difference between maximum and minimum moment of inertia of the region divided by their sum) are used to verify whether the region contains a defect or is defect-free. The contour of the region is then simply represented by the convex hull (for knot) or a polygon (for crack). Figure 7 shows the final retained defect-like regions with holes and gaps filled.

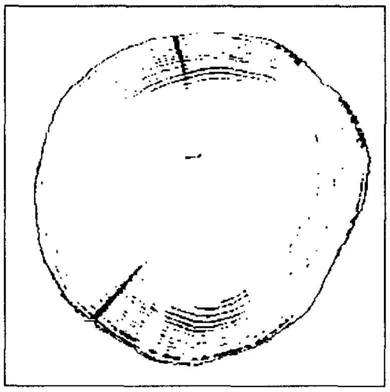

Figure 5. The first class in the smoothed image.

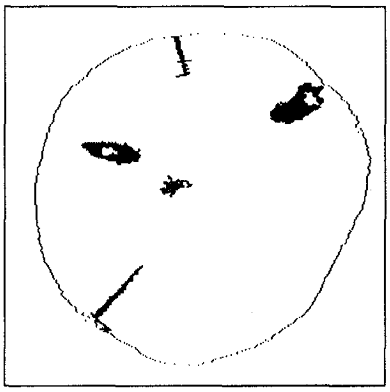

Figure 6. Retained defect-like regions.

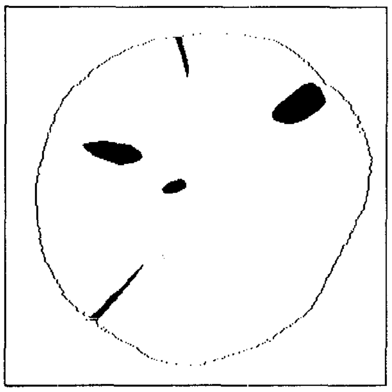

Figure 7. Final detected defects.

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4. 3-D analysis of defect-like regions across CT image slices

The ultimate objective of the system is to detect log defects from a series of CT images. So we need to reconstruct 3-D defects from the 2-D defect-like regions to verify if they indeed constitute valid defects. Since logs are from living trees, their physical condition as well as the biological characteristics of the trees result in a large variation in the CT images. A spot in a CT image may be deemed as a part of a defect, but actually may be caused by a variation in the physical condition in this portion of the wood. For example, Figure 9a is a CT image of Hard Maple. From this image and its neighboring images, the bright spot (actually caused by high local moisture content) in the lower right corner at first was considered as a knot. But after the log was cut, no knot was found in this section and a later CT image of the dried wood showed no bright spot (Figure 9b). Thus it is necessary to discard defect-like regions if they have no corresponding defect-like regions in neighboring CT images to constitute a valid 3-D defect (i.e. an isolated defect-like region or falsely retained region) or even if they do have corresponding neighboring defect-like regions, these regions constitute a false defect. In fact, using knowledge of wood science, most of the ambiguity could be resolved by a 3-D analysis of defect-like regions across successive CT image slices.

4.1 Preliminary grouping of defect-like regions

To implement the 3-D analysis efficiently, preliminary groups of defect-like regions are generated from the defect-like region list using an iterative procedure and two essential geometric parameters α and r (Figure 8). Each group essentially is a series of defect-like regions that are spatially connected across CT image slices and may be classified as a defect if it passes the 3-D test. The minimum number of regions in a group is three for a knot-like group, and ten for a crack-like group. These numbers are dependent on the minimum size of the defect to be detected and the scanning parameters employed.

4.2 Measurement of 3-D defect parameters using successive CT image slices

A knot is a branch that is embedded in the wood of a tree trunk. The branch angle, which refers to the angle between the branch pith line and the tree trunk pith line, is often around 45 degrees. This angle, measured between the log pith line and the defect-like region's center line, is the most important factor in distinguishing a knot from other bright objects, such as a water pocket (Figure 9a and Figure 10b). Other slightly less important 3-D measurements for the knot-like group include the change in region area across successive CT image slices, and the region shape. For a normal knot, the area should change from small to large to small along successive CT slices containing the knot, and the region shape is oval for most knots.

For the crack-like group, a 3-D region orientation measurement and the measurement of the angle between the pith line and the region center line may be adequate to determine whether the group is a crack or not.

5. Conclusions and future research

The algorithm described above works well for detecting knots and cracks in relatively regular CT log images (such as Figure 2) for a variety of hardwood logs including red oak, black walnut, and hard maple , which are representative species of ring porous, semi-ring porous, and diffuse porous wood, respectively. The algorithm is not very effective for images with irregular defect shapes, with very dense annual rings where the width of the rings is less than the scanner spatial resolution, and with low density variation between normal wood and defects (such as Figure 11). In addition, other defects such as rot also need to be detected. Algorithms for linking annual ring structures in an edge detected image are topics under current investigation. Such an edge linker, if successfully implemented, would reveal most defect-like regions where there are a lot of broken rings left unlinked or where the ring direction changes rapidly and/or frequently.

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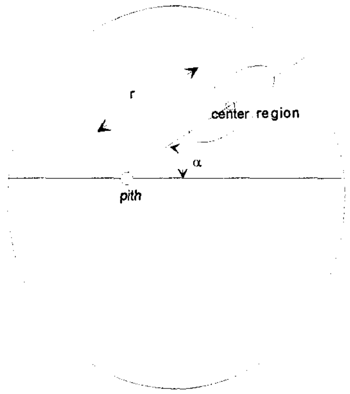
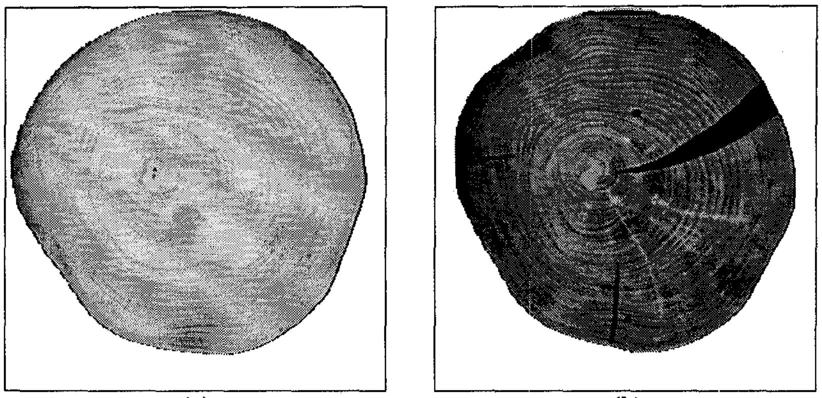
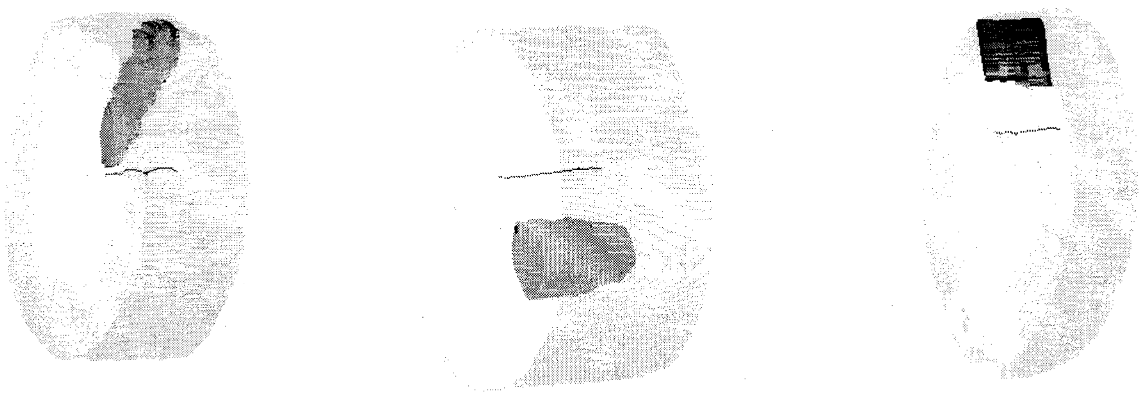


Figure 8. The two geometric values used to group the defect-like regions.



(a) (b)

Figure 9. (a) The bright spot in the lower right corner is caused by high local moisture content.
(b) A later scan of the dried log sample shows a very different image.



(a) (b) (c)

Figure 10. (a) A portion of Oak shows a knot detected. The branch angle is about 46 degrees.
(b) A portion of Maple shows a water pocket. The angle between pith line and region center line is about 3 degrees.
(c) A portion of Oak shows a crack detected.

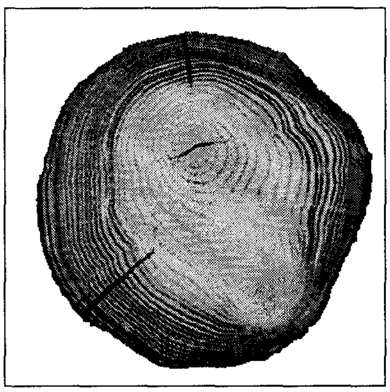


Figure 11. An image of Oak may cause the segmentation algorithm to fail to retain the knot region.

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