# CT IMAGING OF HARDWOOD LOGS FOR LUMBER PRODUCTION

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## ABSTRACT

Hardwood sawmill operators need to improve the conversion of raw material (logs) into lumber. Internal log scanning provides detailed information that can aid log processors in improving lumber recovery. However, scanner data (i.e. tomographic images) need to be analyzed prior to presentation to saw operators. Automatic labeling of computer tomography (CT) images is feasible, but no research has established labeling accuracy or demonstrated real time operation. An automated labeling scheme is presented in this paper that is both very accurate and very fast. The procedure segments and classifies each pixel in a CT image as either knot, split, bark, decay, or clear wood by using a small 3D pixel neighborhood as input to an artificial neural network classifier. Initial results with two species of oak and with yellow poplar indicate that species-dependent classifiers of this type can be constructed. This classification approach can also be applied to other types of images encountered in industrial inspection applications, e.g., gray-scale and color images.

## KEYWORDS

Classification, image processing, machine vision, industrial inspection, artificial neural network.

## INTRODUCTION

Knowledge of internal log defects, obtained by scanning, is a critical component of efficiency improvements for future mills (Occeña 1991). Studies (Richards and others 1980, Tsolakides 1969, Wagner and others 1990) have demonstrated potential value gains of 11%, 14%, and 21%, respectively, that can be achieved by sawing logs under different log orientations and using different sawing methods. A basic assumption for the application of nondestructive evaluation to log sawing is that knowledge of internal defects will lead to choice of the best sawing position and method, and therefore will allow mills to realize these potential value gains.

Before computer tomography (CT) scanning or any other type of internal log scanning can be applied in industrial operations, there are several hurdles that must be overcome. First, there needs to be some way to automatically interpret scan information so that it can provide the saw operator with the information needed to make proper sawing decisions. For the purposes of sawing the log cylinder into high-value boards, this means accurately locating, sizing, and labeling internal defects. Second, this defect recognition procedure must operate at real time speeds, so that scanning, image reconstruction, and image interpretation and display can be integrated into mill processing. Third, a 3D display

of a log and its defects for the sawyer is only the first step toward real efficiency. Eventually, the sawyer must be guided by computer-analyzed suggestions for the best log breakdown sequence, or have the sawing completely controlled by computer processing.

The work described here addresses the first and second of these processing needs. The next section discusses previous work on these topics. This is followed by a general description of the neural-net based classification technique that we have developed. Following a description of our experimental methods, performance results are given, including a qualitative comparison with previous approaches. The final section contains conclusions that we have drawn from this work, and some directions for further research.

## PREVIOUS WORK

Because most defects of interest are internal, a nondestructive sensing technique is needed which can provide a 3D view of a log's interior. Several different sensing methods have been tried, including nuclear magnetic resonance, ultrasound, and x-ray. Due to its efficiency, resolution, and widespread application in medicine, x-ray computed tomography has received extensive testing for roundwood applications (e.g., Funt and Bryant 1987, Som and others 1992, Zhu and others 1991b). As noted above, however, CT images require computer analysis before they can be useful in an industrial setting.

Previous work on automatically labeling internal log defects established the feasibility of utilizing CT images. These researchers employed a variety of methods to segment different regions of a CT image and then to interpret, or label, those segmented regions. Often, image segmentation methods are based on threshold values derived from image histograms (Som and others 1992, Zhu and others 1991b). Texture-based techniques have been applied to defect labeling only (Funt and Bryant 1987, Zhu and others 1991a), not segmentation. Knowledge-based classification (Zhu 1993), shape examination (Funt and Bryant 1987, Som and others 1992), and morphological operations (Som and others 1992) have been used to label defects, also.

While previous efforts have demonstrated feasibility, they have some serious limitations. First, reports of defect labeling accuracy are often either anecdotal, based on success in a training set, or based on a single test set. No statistically valid estimates of labeling accuracy can be found in the literature. Second, there has been no effort to assess or to achieve real-time operability of the developed algorithms. Third, texture information is critical for human differentiation of regions in CT images (i.e. image segmentation), and

automated recognition algorithms should exploit this fact for computer-based processing.

These limitations are addressed by a new approach described below. In contrast to global approaches that separate the tasks of segmentation and region labeling, our approach operates using local pixel neighborhoods primarily, and combines segmentation and labeling into a single classification step using a feed-forward artificial neural network (ANN). To accommodate different types of hardwoods, a histogram-based preprocessing step normalizes CT density values prior to ANN classification. Morphological postprocessing is used to refine the shapes of detected image regions. These steps are described in the next section.

## METHODS

The CT image interpretation system that has been developed here consists of three parts: (1) a preprocessing module, (2) a neural-net based classifier, and (3) a post-processing module. The preprocessing step separates wood from background and internal voids, and normalizes density values. The classifier labels each non-background pixel of a CT slice using histogram-normalized values from a 3×3×3 window about the classified pixel. Morphological operations are performed during post-processing to remove spurious misclassifications.

### Preprocessing - Background Thresholding

The first objective of preprocessing is to identify background regions, so that these regions can be ignored by the classifier. Our initial approach was to extract histograms for individual CT slices and apply Otsu's thresholding method (Otsu 1979). This method assumes bimodal histograms, and minimizes within-group variance. In our application, it automatically determines a correct threshold for many CT log images (Figure 1), because the histograms are typically bimodal. The two peaks can be found at very low gray-level values (background) and at relatively high CT values, corresponding to clear wood and high-density areas, such as knots and bark. Figure 2 illustrates this with a histogram of densities for the CT slice shown in Figure 1.

Unfortunately, one of the defect types–decay–has density values which are roughly the average of background (air) and clear wood density values. This appears as a small peak in Figure 2, near the midpoint of the two larger peaks. If Otsu's method is applied directly to this histogram, the threshold indicated by $t_1$ is detected, causing decay regions to be treated as background. We address this problem by weighting the histogram values, using the function

$$w(t) = 1 - e^{-(\frac{t - t_1}{b})^2} \qquad (1)$$

where $t_1$ is the threshold determined by applying Otsu's method initially, and $b = 2000$. This value for $b$ was chosen experimentally. When Otsu's method is applied to the resulting histogram, the threshold $t_2$ is found, which successfully distinguishes decay from background. This method has been tested using a large number of CT samples. The weighting function modifies histogram values only for the purpose of determining a threshold value for background pixels. The original pixel CT values are not modified in this step.
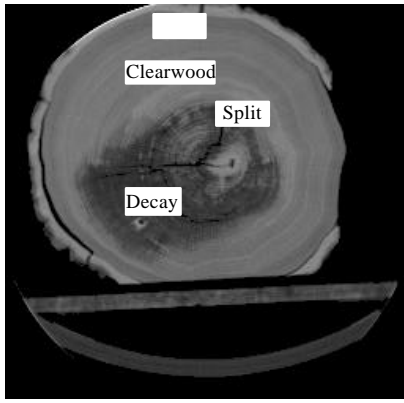


Figure 1. Different densities are depicted by different gray-level values in this computer-generated x-ray tomograph of a red oak log. The slice shown here contains $256 \times 256$ elements, each corresponding to a volume of $2.5 \times 2.5 \times 2.5$ mm$^3$.

Preprocessing - Density Normalization

The second objective of preprocessing is to normalize CT values, so that the classification step can work with different types of wood. Normalization is especially important because neighborhood pixel values are used as features by the classifier. If pixel values are not normalized there will be no consistent relationships among similar regions across CT images, and the ANN classifier will be unable to learn any patterns.

All hardwood CT histograms that we have examined have the characteristics of the histogram in Figure 2. That is, there is a large peak of background pixel values at the far left, a large peak of clear wood, bark, and knot pixel values at the far right, and decay pixel values (if present) located at approximately the midpoint of the clear wood values.

To ensure consistency of defect region values across images, we want to be able to do several things with any histogram of CT density values. First, we want to

shift the rightmost peak–containing clear wood, bark, and knot values–so that these regions always have the same values and so that the shape of this peak does not change. Second, we want the lower CT values, representing background, to remain about the same following the transformation, so that zero values stay near zero. Third, we want the CT values between the leftmost and rightmost peaks for each original histogram to have the same relative position in a transformed histogram. This type of transformation will give the important regions of any CT image the same density values, and allow us to apply our pixel-value dependent classifier to those normalized values.
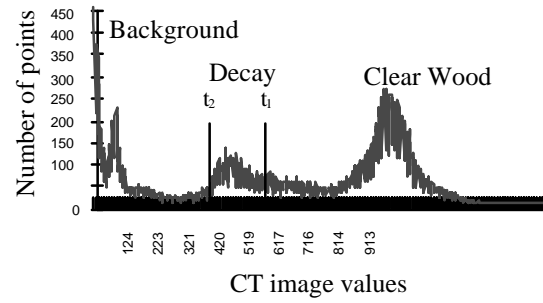


Figure 2. Background pixels produce a very large peak in this histogram, part of which is omitted from the figure to improve clarity. The $t_1$ threshold is obtained using Otsu's method directly; $t_2$ is obtained after introducing a weighting function to the histogram.

The method used here applies a transformation to each CT value in the image. The transformation includes two components: (1) a variable translation component and (2) normalization by an arbitrary parameter. The transformation function is given in Eq. 2.

$$x_t = \frac{x_o + f(x_o ; x_{cw})(x_a - x_{cw})}{x_a} \qquad (2)$$

where

$x_t$      transformed CT value

$x_o$      original CT value

$x_{cw}$      original CT value of clear wood peak

$x_a$      arbitrary translation anchor value, greater than the CT value of the clear wood peak

$f$      translation multiplier

The translation anchor $x_a$ is an arbitrary parameter selected to be greater than the CT value of the clear wood peak. The rightmost histogram peak (including clear wood, knot, and bark values) will be shifted to the

right by the amount $x_a - x_{cw}$, so that the clear wood peak is now at $x_a$. The resulting values are normalized by $x_a$ so that the clear wood peak of a normalized histogram is always located at 1. In order for the translation of the rightmost peak to be consistent for all histograms it is necessary for the translation anchor value to be the same for all histograms. Otherwise, the shape of the rightmost peak will change with respect to the range of transformed density values. Greater details of this histogram normalization procedure can be found in Schmoldt and others (1995).

## A Neighborhood-Based Neural-Net Classifier

A multilayer feed-forward neural network is used to perform the primary classification step. There were two initial goals in this research: (1) to determine if the tasks of segmentation and region labeling could be combined into a single step and (2) to determine whether an ANN classifier could perform well using only simple features obtained from local neighborhoods. Aside from the initial background thresholding, both segmentation and defect labeling are performed simultaneously by the classifier.

Each histogram-normalized value in a 3×3×3 neighborhood about the target pixel serves as an input to the ANN. One additional input is the "radius" of the element under consideration, which is the distance of the target pixel from the centroid of the foreground region of the CT slice. This distance measure provides contextual information that aids in classification. Some entities (such as splits) tend to lie near log centers and others (such as bark) lie near the outside edge of the log. Gross splits can be identified by background thresholding. Narrower splits are subresolution and must be classified by the ANN using local neighborhood information. There are 5 output nodes of the ANN, one for each of the classes to be detected: knot, split, bark, decay or clear wood. The class associated with the output node that has the largest value is selected as the classification.

The network was trained using the conventional back-propagation method. Because network topology has a large impact on classification accuracy and on convergence time during training, several topologies were compared. Networks using one, two, and three hidden layers were generated, with the total number of weights for each network topology kept constant (Özkan and others 1993).

At this date, the image interpretation system has been trained using only two hardwood species, northern red oak (*Quercus rubra*, L.) and water oak (*Quercus nigra*, L.). The training/testing example set was selected from multiple CT slices and consists of 1973 samples. Ten-fold cross-validation was used to estimate the true accuracy rate of the ANN classifier.

## Postprocessing

Because local neighborhoods are the primary source of classification features that are used by the ANN, spurious misclassifications tend to occur at isolated points. A post-processing procedure is used to remove small regions, thereby improving overall classification accuracy. This method is effective since the defects of interest typically have relatively large sizes in an image. We chose to use the gray-scale operations of erosion followed by dilation for this purpose. A 3×3 structuring element is used for both operations. An added benefit is that labeled region borders are smoothed somewhat during this process.

## RESULTS

Four different ANN topologies were trained/tested using ten-fold cross-validation. The results are shown in Table 1. The ANN with two hidden layers exhibited the best performance with an accuracy of just under 95% for pixel classification. The next best classifier, with a single hidden layer of 12 nodes, exhibited practically the same classification accuracy. Because the latter network requires much less processing time, it was chosen as the optimal classifier among those evaluated. It is interesting to note that classification performance decreased slightly as the number of hidden layers increased.

| Network topology | Number of weights | Number of training iterations | Classification accuracy |
|---|---|---|---|
| 28-12-5 | 396 | 6699 | 0.947795 |
| 28-10-8-5 | 400 | 8299 | 0.949316 |
| 28-7-16-5 | 388 | 10499 | 0.939686 |
| 28-8-8-8-5 | 392 | 60499 | 0.853523 |

Table 1. Network performance varies with topology.

The chosen classifier has been applied to two CT images for illustration (Figure 3). As anticipated, the ANN produces some isolated pixel misclassifications, as shown in the middle column of the figure. The classification regions are improved with post-processing, however, as shown at the right. In the second example of Figure 3, for example, the ANN classified partial regions of several growth rings as split defects; these were removed by subsequent postprocessing. In the first example in that figure, incorrect labels near the border of the CT slice are removed by postprocessing steps.

The image interpretation system is currently implemented on a desktop computer containing a 33MHz processor. Analysis of a single 256×256 CT slice requires about 25 seconds. This is considerably faster than the previous approach (Zhu 1993) which requires 9 minutes of processing time on a VAX 11/785. Because the algorithms are implemented in C, however, they can be transported easily to any other computer hardware.

In comparison to previous hardwood log inspection systems, our system has a simple implementation, but high classification speed and accuracy. Other systems are reported to be able to successfully identify or locate some internal defects, but few statistical results are available. Most previous work is limited to 2D image analysis, which does not make full use of the 3D nature of CT images. Finally, most research has dealt with a single type of wood, whereas our approach successfully deals with two different wood species.

## CONCLUSIONS

In general, the ANN classifier, operating primarily with local, pixel values, is able to classify regions of CT images with 95% accuracy at the pixel level. Postprocessing improves this value considerably, but we do not have an exact numerical estimate for this improvement. Most regions are detected and correctly labeled; however, in some cases the classifier fails to correctly size defects. It is possible that by the addition of further postprocessing, e.g., high-level, rule-based analysis of defect regions, we may be able to size defects more accurately and to remove any remaining misclassified regions.

As noted above, the entire classification operation requires only about 25 seconds on the current hardware. By using newer RISC-based hardware, this defect recognition time can be reduced drastically, by a factor of 8-10. This places defect recognition speed on a par with scanning and image reconstruction times. Because each of these 3 operations takes 2-3 seconds, they can be performed in parallel on successive slices. Therefore, this defect recognition technique can easily be implemented in real time as logs are scanned and images reconstructed.

Because of the success of the trained ANN classifier on oak samples, we feel confident that we can develop species-dependent classifiers that are very accurate. It is not clear, however, whether we will be able to create a classifier that is entirely independent of species. Should a generalized classifier prove to be infeasible, species-dependent classifiers can still be useful in actual mill operations because typically a single species is sawn over an extended period.

Although we have limited our investigations to 3D CT images of hardwood logs, it appears that the image analysis methods described here can extend to other applications and data types. Initial results using a 2D classifier produced only slightly lower classification accuracy than using 3D data. Therefore, we feel that the same approach will work well with gray-scale video images, sonograms, and other 2D data types. For applications involving color video images, it should be possible to treat the red, green, and blue images as separate "slices" which provide input to the ANN. Depending on the application, the ANN may produce final classification, or it may transmit information to a subsequent processing stage for higher-level analysis.

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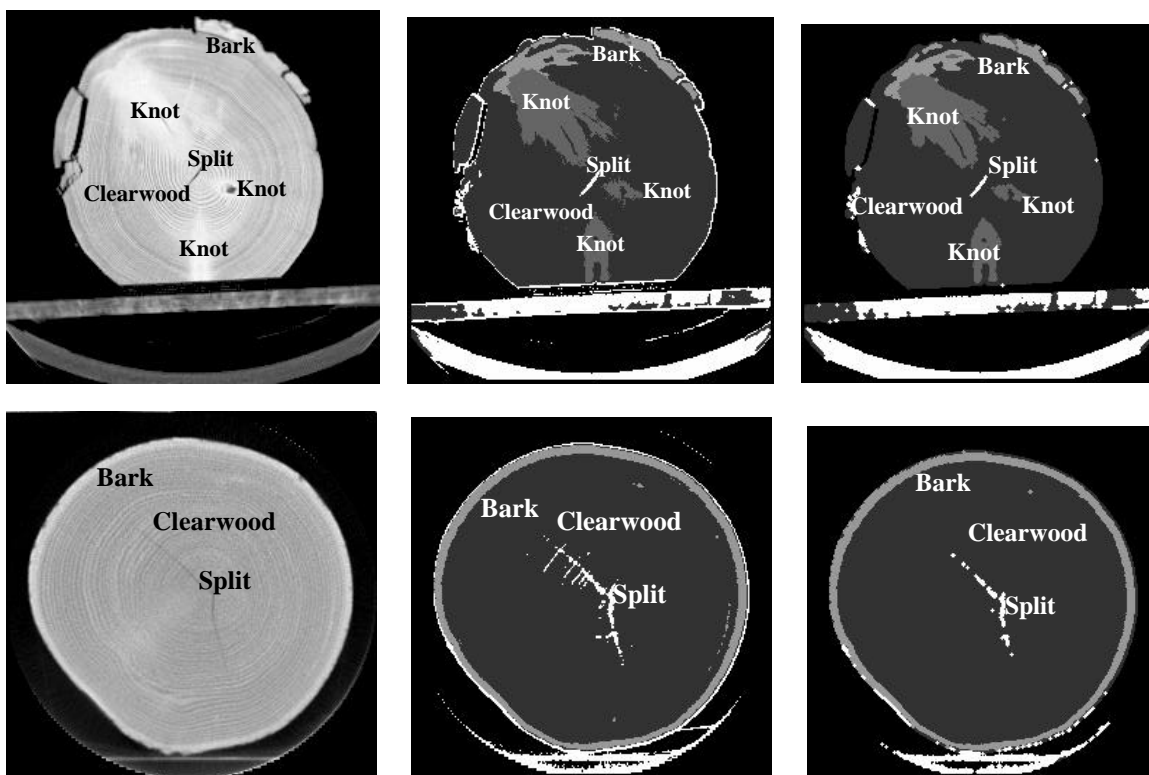
Figure 3. Two log CT images demonstrate defect recognition results. Original CT images appear at the left, middle images are ANN classified images, and the rightmost images depict the classification results following postprocessing.

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