Automated Analysis of CT Images for the Inspection of Hardwood Logs

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Abstract **--This paper investigates several classifiers for labeling internal features of hardwood logs using computed tomography (CT) images. A primary motivation is to locate and classify internal defects s o that an optimal cutting strategy can be chosen. Previous work has relied on combinations of low-level processing, image segmentation, autoregressive texture modeling, and knowledge-based analysis. Most previous work has also been limited to two-dimensional analysis of a single species only. This paper describes these approaches briefly, and compares them with a feed-forward neural-net classifier that we have developed. In order to accommodate species with different cell anatomies, CT density values are first normalized. Features are then extracted, primarily using local three-dimensional data, Somewhat surprisingly, this Iocality approach has resulted in a pixel-by-pixel classification accuracy of 95%. This accuracy improves during subsequent morphological processing steps which refine the detected defect regions in the images.**

I. INTRODUCTION

Before a hardwood log is processed at a sawmill, an assessment of the log's quality is performed. Quality is inversely related to the presence of defects in the wood, such as knots, splits, voids, and decay. Logs with the highest quality are converted to veneer, and the rest are sawed into lumber. When a log is to be sawed, a cutting strategy must be determined which preserves large areas of clear wood on board faces. There is a strong incentive to perform a correct assessment, for both veneer and saw logs, since the economic return can improve considerably (possibly up to a factor of 10) when a correct decision is made [4,9, 11].

Since most defects of interest are internal, a nondestructive sensing technique is needed which can provide a three-dimensional (3D) view of the log's interior. Several researchers have considered the use of x-ray computed tomography (CT) for this purpose, and have established the feasibility of defect detection using CT imagery [1, 2, 8-12]. These researchers have employed texture-based techniques [10], image segmentation methods [11], and knowledge-based classification [9, 12] to locate and classify defects. In most cases, image analysis has focused on a single two-dimensional (2D) CT slice, although in a few cases neighboring slices have been used for 3D filtering during preprocessing steps.

This paper presents an alternative to these methods. A feed-forward artificial neural network (ANN) has been employed to accept CT values from a small 3D neighborhood, and then classify each pixel as knot, split, bark, decay, or clear wood. In order to accommodate different types of hardwoods, a histogram-based preprocessing step normalizes pixel values in each CT image. Following initial classification by the ANN, a postprocessing step is performed to refine the shapes of detected image regions. The major benefits of this classification approach are high computational speed and high classification accuracy. The system has been extensively tested, and ten-fold cross-validation indicates a classification accuracy of 95% by the ANN before postprocessing. The potential for parallelization is high, because local neighborhoods are used, and the classifier can be applied to all pixels in parallel.

The major contributions of this research are as follows: 1) a neural-net classifier has been developed which relies almost exclusively on *local CT* neighborhoods; 2) different neighborhood feature types have been carefully assessed; 3) the classifier normalizes CT density values, and therefore automatically accommodates different hardwood types; 4) a comparison of classification performance using 2D and 3D neighborhoods is given; and 5) several different ANN topologies have been carefully tested.

The next section presents the primary issues involved in CT-based hardwood log inspection. Section III describes previous work. Section IV presents the ANN-based system, and Section V contains performance results, including a comparison with previous approaches. Section VI summarizes the paper.

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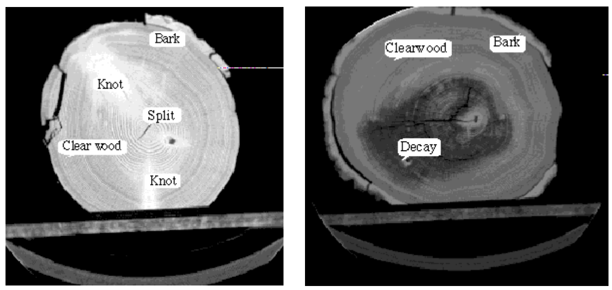
II. LOG INSPECTION AND CT IMAGING

Hardwoods are popular as materials for furniture and fine woodworking due to their rich, colorful grain. Because visual appearance is a primary consideration, a “defect” is anything that adversely affects the wood’s aesthetic appearance. Although a large number of defect types have been cataloged, those of primary interest in this research are knots, splits, decay, and bark.

It is natural to consider tomographic techniques for this inspection task, because these defects need to be detected internally and because they tend to differ in density from the surrounding clear wood. CT imaging was first introduced as a medical diagnosis technique, but is gaining in popularity in nonmedical applications such as the inspection of concrete, steel, wood, and paper rolls [1, 9]. As shown in Figure 1, an x-ray CT scanner produces image slices that capture many details of a log’s internal structure. Each slice shown here contains 256×256 elements, each corresponding to a volume of $2.5 \times 2.5 \times 2.5$ cu. mm. Examples of hardwood defects are indicated in the figure. CT numbers are directly related to density, and CT images therefore vary dramatically for different species and by moisture content. Therefore, a log that is freshly cut will produce different CT values than one that has had time to dry. Because of the large amount of data obtained with a CT scan of a single log (often several hundred megabytes), a practical evaluation system requires simple, high-speed image-analysis algorithms [3].



(a) (b)

Figure 1. Sample CT images from two different red oak logs. Regions containing defects and clear wood are indicated.

III. RELATED RESEARCH

Although much effort has been devoted to CT image analysis in the medical field, only a few researchers have considered CT-based inspection in the forest products industry. Funt and Bryant [2] designed a system that analyzes CT scans of sawlogs. Using 2D image interpretation techniques, the system uses density, shape, and texture information to identify background, clear wood, and defect regions. Since the background (air) is low in density, it can be easily identified. Texture analysis aids in identifying growth ring patterns, and this is used to classify clear wood regions. Knots are detected as regions having higher density than the surrounding clear wood, and by evaluating the shape of the region. Classification accuracies are not reported.

More recently, Zhu, Conners, and Araman have described a knowledge-based vision system that is capable of locating, identifying and quantifying the internal defects of logs by analyzing CT image data [9, 11, 12]. The system is composed of three modules: a data acquisition unit, an image segmentation module, and a scene analysis module. The image segmentation module performs the tasks of image filtering, segmentation, region detection and merging, and 3D volume growing. The scene analysis module performs log defect recognition using Dempster-Shafer techniques. The image segmentation module can separate regions of clear wood from defect regions (knots, splits, holes, decay, and bark), and the scene analysis module labels the defect regions. The system has been tested with two hardwood species, and it is suggested by the researchers that more work is needed in order to accommodate additional hardwood species.

Zhu, Beex, and Conners [10] proposed a stochastic field-based approach for wood texture analysis. In this approach, CT images are first segmented, as described above . An autoregressive modeling algorithm is then used to recognize defect regions. It is reported that this texture modeling method can discriminate knots, barks and decay. All experiments were done using images of red oak samples.

IV. A NEURAL-NET BASED APPROACH

The CT image interpretation system that has been developed here consists of three parts: a preprocessing module, a neural-net based classifier, and a post-processing module. The preprocessing step separates wood from background and internal voids, and normalizes density values. The classifier labels each pixel of a CT slice using

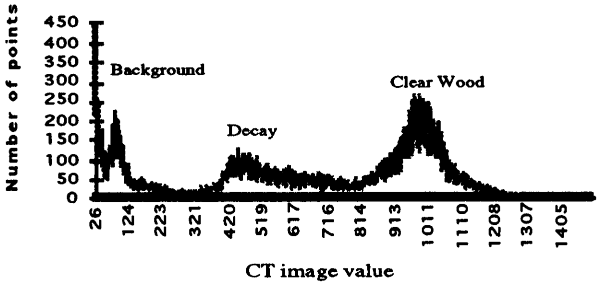


Figure 2. Histogram of the log section shown in Figure 1(b). For clarity, the large background peak has been partially omitted.

A. Preprocessing

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 [6]. This method assumes bimodal histograms, and minimizes within-group variance. In our application, it automatically determines a correct threshold for many CT log images, since the histograms are typically bimodal. Unfortunately, one of the defect types-decay-has density values which are roughly the average of background (air) and clear wood density values. This is illustrated in Figure 2, which contains a histogram *h* of densities for the CT slice shown in Figure l(b).

In Figure 2, the rightmost histogram peak represents clear wood and bark. Knots rae denser than clear wood, and tend to cluster at the right side of this peak when present. A large peak representing background is partially shown at the left. Decay values cause a small peak to appear near the midpoint of the two larger peaks. If Otsu's method is applied directly to this histogram, part of the decay peak at the left side will be classified as background. We therefore apply the following weighting function w:

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

The quantity t is a CT density value, t_1 is the threshold determined by applying Otsu's method initially, and b is a constant that was chosen experimentally. The modified histogram is $h'(t) = w(t)h(t)$. *The* effect of this weighting is to remove the decay peak and reduce the size of the clear wood peak relative to the background peak. If Otsu's method is applied to h', a new threshold is found to the left of the decay peak so that decay pixels are retained when the background is removed. Note that this weighting is used only for the purpose of choosing a threshold value. The original CT values are not modified in this step. 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 since the resulting density (pixel) values are used directly by the ANN, as described below. If pixel values were not normalized, then logs with even modest differences in moisture content or intrinsic density characteristics would be classified very differently. To ensure consistency of defect region values, we developed the transformation

$$x_{norm} = \frac{1}{x_a}\left[x_0 + \frac{x_a - x_{cw}}{1 + \exp a\left(\frac{x_{cw}}{2} - x_0\right)}\right] \qquad (2)$$

which maps original CT values x_0 to normalized values x_{norm} giving roughly the same density values to important regions of CT log images. This allows us to used an ANN classifier that has been trained using these normalized values. In this equation, the translation anchor x_a is arbitrarily selected to be greater than the CT value of the clear wood peak x_{CW} for any scanned log. The quantity a is an empirically determined constant. Intuitively, small and large values of x_0 pass through (almost) linear mappings, whereas values of x_0 near $x_{CW}/2$ are expanded into a larger range of values. Perhaps most importantly, the clear wood peak is mapped approximately to the normalized value 1.0 for all CT scans.

B. A Neighborhood-based Neural-Net Classifier

Using normalized CT values, we have successfully used a multilayer feed-forward neural network to perform the primary classification step. An initial goal in this research was to determine whether an ANN classifier could perform well using only simple features obtained from small, local neighborhoods. We have found that such a classifier works quite well, although performance is improved if information concerning distance from the center of the log slice is included. This provides contextual information that aids in classification, because some entities (such as splits) tend to lie near log centers and others (such as bark) lie near the outside edge of the log.

We have tested this approach using CT images from several scanned logs using 3x3x3 windows. Each histogram-normalized value in the neighborhood serves as an input to the ANN. One additional input is the radial distance of the pixel under consideration from the centroid of the foreground region of the CT slice, for a total of 28 input nodes. There are 5 output nodes of the ANN, one for each of the classes to be detected. The class associated with the output node that has the largest value for a given input is selected as the class label for the current pixel.

The network was trained using the conventional backpropagation method, with a data set of 1973 points from CT slices of two different species of oak. Because network topology has a large impact on classification accuracy and on convergence time during training, several network 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 [5, 7]. Each was trained using the same data set, and ten-fold cross-validation was performed for each neural network classifier to assess classification accuracy. The results are shown in Table 1, where the ANN with two hidden layers exhibited the best performance with an accuracy of almost 95%. The next best classifier, with a single hidden layer of 12 nodes, exhibited practically the same classification accuracy. Because it requires much less processing time, it was chosen as the optimal classifier among those evaluated. It is interesting to note that classification performance decreased dramatically when a network with three hidden layers was used.

Table 1. Network Topologies and Classification Performance

Topologies	**Total 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

All of the neural networks considered here were trained by the delta rule with a momentum term. The effect of learning parameters on the speed of training convergence was studied by experimenting with various learning rates and momentum terms, as shown in Figure 3. It was observed that for a small learning rate, the momentum term has a relatively large impact on the convergence speed. But when the learning rate increases, the impact decreases gradually. The final choice of the learning parameters is a small learning rate (0.1) and a medium momentum term (0.6). Experiments using different initial weights to train the networks show that the choice of initial weights has a negligible effect on the training process and on the performance of the classifier.

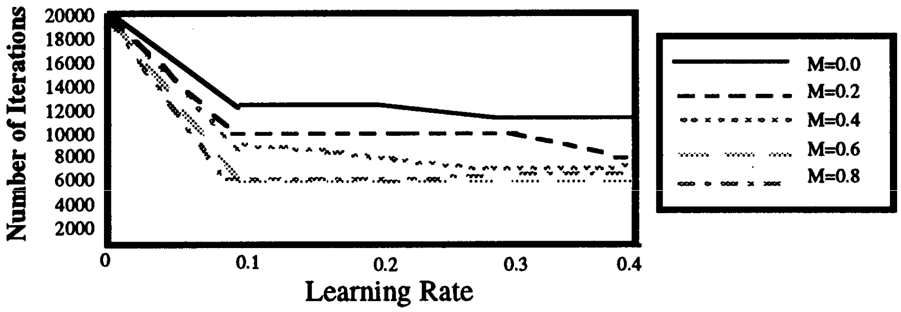


Figure 3. Convergence time vs. the two learning parameters. *M* represents the momentum term.

Finally, we compared this 3D classifier with a similar ANN which used 2D CT neighborhoods only. Using only 9 pixels from a 2D neighborhood along with the radial distance input, classification accuracy dropped from 94.7% to 93.7%.

C. *Post-processing*

Because local neighborhoods are the primary source of classification features, spurious misclassifications tend to occur at isolated points. A post-processing procedure is used to remove small regions, thereby improving overall system performance. We chose to use the morphological operations of erosion followed by dilation for this purpose. An added benefit is that labeled region borders are smoothed somewhat during this process.

V. RESULTS AND COMPARISON

At this date, the image interpretation system has been tested with two hardwood species, northern red oak *(Quercus rubra,* L.) and water oak *(Quercus nigra,* L.). Although these two species are from the same family of oaks, they *are* from different geographic regions and growing conditions. Training/testing samples were selected from multiple CT slices. Ten-fold cross-validation was used to estimate the true accuracy rate of the ANN classifier, and a final classification accuracy of 95% was observed. Post-processing improved this rate still tither.

Four examples of classified log sections are shown in Figure 4. These examples were chosen because they exhibit all defects of interest. The fourth example is from a yellow poplar log, which was not used for training. Despite this, the classifier was able to distinguish bark, clear wood, and knots quite well, even thought the knot area was not correctly sized. As anticipated, isolated pixel misclassifications exist. The classification regions are improved with post-processing, as illustrated in the third column of Figure 4. For example, in the fourth row, the ANN classified several partial rings as split defects, although most of them were removed by subsequent processing. In the upper examples in that figure, incorrect labels near the outside border of the CT slices are removed by postprocessing steps.

This image analysis system has been implemented on a Macintosh Quadra 650 containing an MC68040/33MHz processor. Analysis of a single 256x256 CT slice requires about 25 seconds. Using faster hardware this time can be further reduced by an order of magnitude. This implementation shows high potential for parallization since only local features are used.

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 three different wood species.

VI. SUMMARY

This paper presents an assessment of techniques for hardwood log inspection using CT images. A neural-network classifier has been developed and carefully tested, and its performance has been compared with previous classification methods. Several feature types have been evaluated, and several feed-forward neural-net topologies have been considered.

The primary advantages of this classification method are high speed and accuracy. Because it relies primarily on CT density values from local 3D neighborhoods, it is simple to implement, and is a good candidate for parallelization. The high classification accuracies produced by the neural net improve with region refinement during post-processing. It is expected that this approach can be used effectively for other applications in which CT image analysis is employed.

VII. ACKNOWLEDGMENTS

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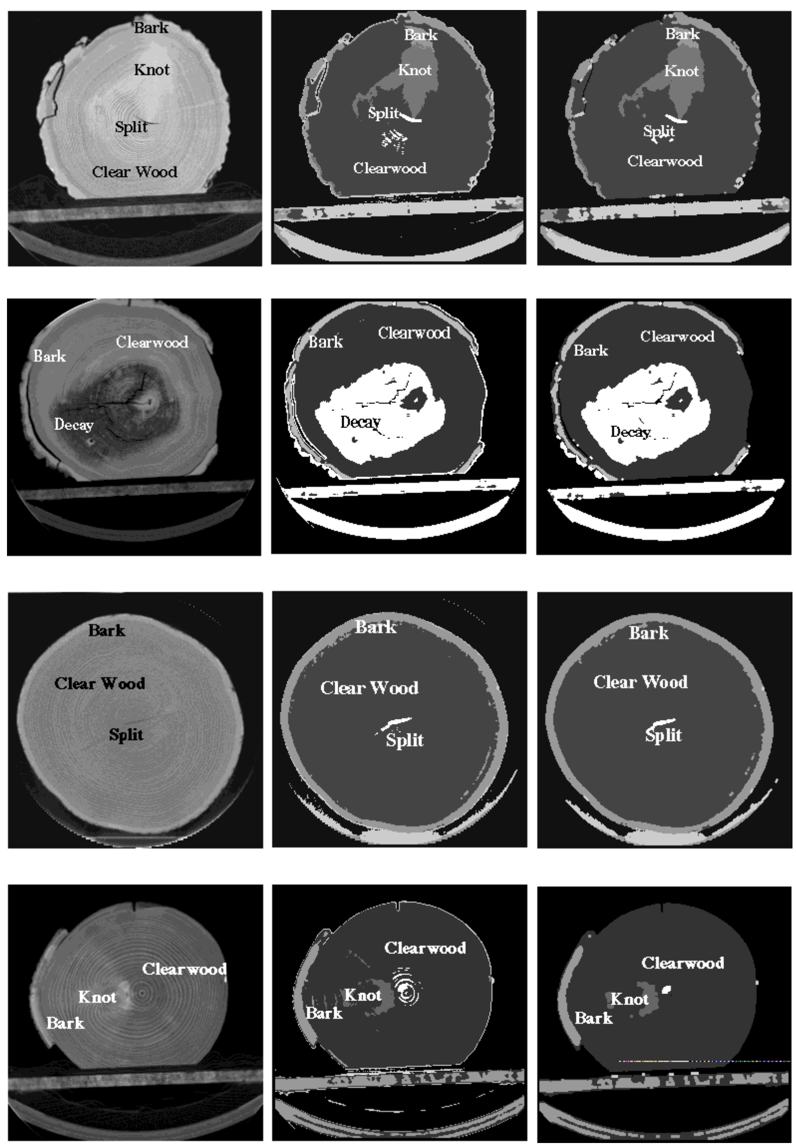

Figure 4. Four log CT images demonstrate defect recognition results. Original CT images appear at the left in each row. Middle images are ANN classified images, and the rightmost images depict the classification results following postprocessing. The top 3 examples are oak and the bottom example is yellow poplar.

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