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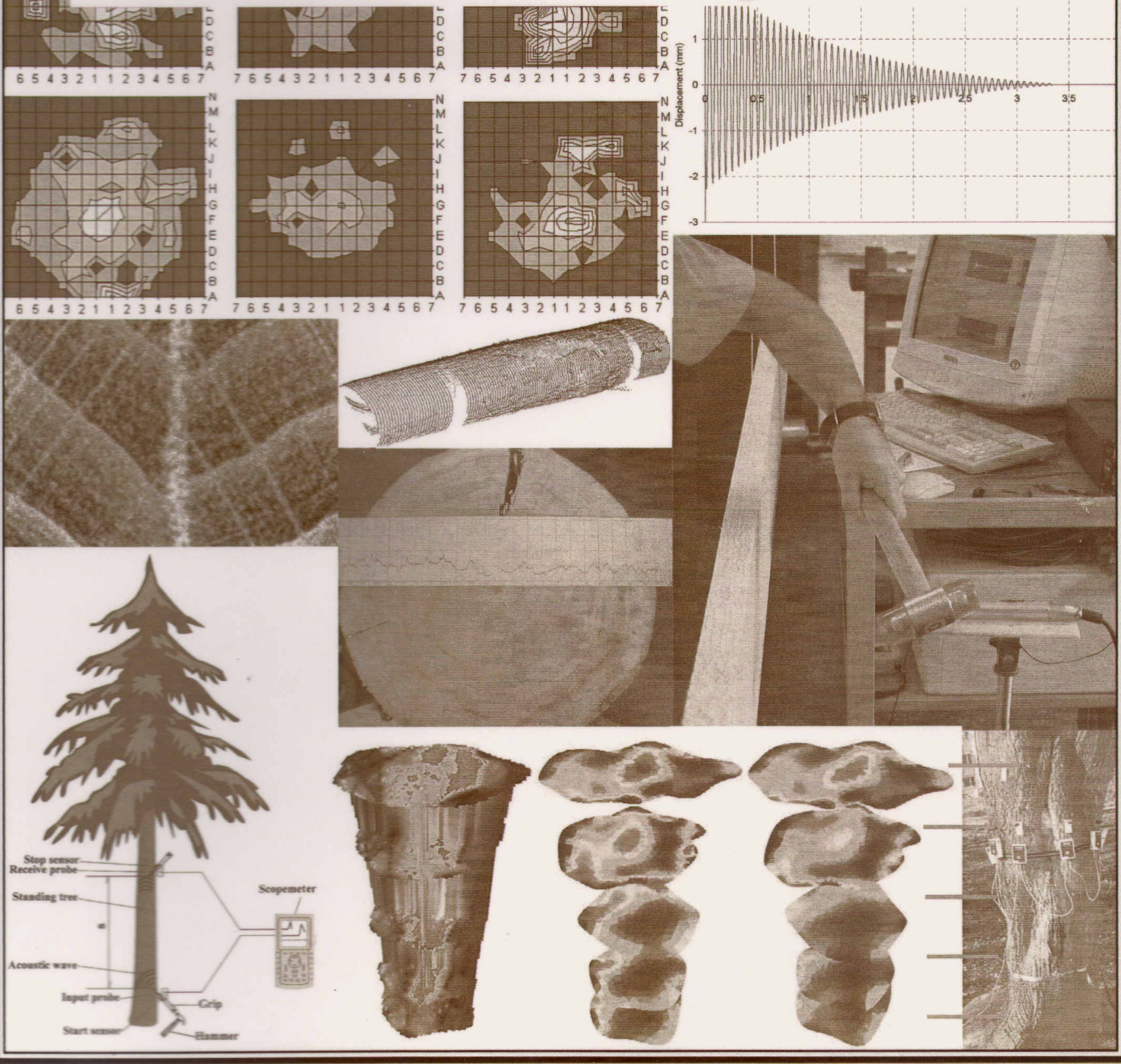

# Defect Detection in Hardwood Logs Using High Resolution Laser Scan Data

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## Abstract

The location, type, and severity of external defects on hardwood logs and stems are the primary indicators of overall log quality and value. External defects provide hints about internal log characteristics. Anticipating the location and characteristics of internal log defects prior to log breakdown promises to dramatically improve the production of lumber in terms of both quality and quantity. Using industrial scanning components, a high-resolution laser scanning system has been constructed in Princeton, West Virginia, to examine the potential of laser scanning for defect detection. To date, 162 red oak and yellow-poplar logs have been scanned and processed. Using robust circle or ellipse fitting methods, a residual image is extracted from the laser scan data. The log "skins" in the residual images show most bark texture features and surface characteristics of the original log or stem. Defects with height differentiation from the background log surface can be distinguished. Using simple shape definition rules combined with the height map allows most severe defects to be detected. Defects can be detected by determining the contour levels of a residual image. Pattern recognition methods, such as cluster analysis, are used to classify different defect types. With the exceptional resolution of the current scanner, we plan to examine bark texture changes such that adventitious buds, minor distortions, and other defects not associated with a height change might be detected.



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## Introduction

Before a hardwood log is processed, it is visually assessed and the number and type of external defects noted. The difference between high and low quality logs is determined by defect type, frequency, size, and location. It is difficult to accurately and rapidly detect and measure defects, either mechanically or manually (Tian and Murphy 1997). But, optimizing the breakdown of the log into products is a crucial step. The value of the lumber that can be recovered depends on the presence and location of defects. This is especially true for hardwood logs. In the production of hardwood lumber, boards are sawn to fixed thicknesses and random widths. Since the presence, size, and placement of defects on the boards affect board quality and value, much attention is focused on log surface defects during processing.

For every surface indicator there is almost always an associated internal defect. External defect indicators (on the surface of the log, as opposed to the log ends) are bumps, splits, holes, and circular distortions in the bark pattern. Bumps usually indicate overgrown knots, branches, or wounds. Some bumps have a cavity or hole in the middle, indicating that the overgrown material has decay or is rotten. Circular bark distortions, or rings around a central flattened area, indicate a branch that was overgrown many years earlier. Surface defects progress from a pruned or broken branch to an overgrown knot characterized by a significant bump and then to a rotten knot or a distortion defect. For some classes of defects, it is possible to accurately predict internal features based on external characteristics.

Studies have demonstrated that the use of external or internal defect data improves cutting strategies that optimize lumber recovery from logs, i.e., preserving the largest possible area of clear wood on a board face (Steele et al. 1994). In Steele et al.'s study, 12 red oak logs were collected and divided into two groups that were as closely matched as possible with respect to log size and quality. Logs from one of the groups were sliced into 0.25-in.-thick discs and the location and size of all defects recorded. The data from the slices were assembled to create virtual logs showing all exterior and interior defects. The logs from the unsliced group were sawn to the best of a sawyer's ability to produce the highest valued lumber possible. The logs in the virtual group were sawn by computer using the available defect information. The logs sawn using the defect information averaged 11.21 percent higher value than those sawn manually without defect information.

Several scanning and optimization systems are available that aid in the sawing of logs into lumber. Two types of defect detection are used on hardwood logs: internal and external. Various internal defect inspection methods have been proposed in the literature based on X-ray/CT (computed tomography), X-ray tomosynthesis, MRI (magnetic resonance imaging), microwave scanning, ultrasound, and enhanced pattern recognition of regular X-ray images (Guddanti and Chang 1998, Schmoldt 1996, Wagner et al. 1989, Zhu et al. 1991). CT and MRI systems provide excellent internal images of logs, but image acquisition is slow and expensive. In addition, variable moisture content and log size can present problems to CT scanning (Bhandakar et al. 1999). Laser-line scanners are commonly used in sawmills to gather information on external log characteristics, e.g., diameter, taper, curvature, and length (Samson 1993). Optimization systems use the laser-profile information to better position the log on the carriage and improve the sawyer's decision-making ability. These systems typically were developed for softwood (e.g., pine, spruce, fir) log processing. But, they are becoming increasingly commonplace in hardwood mills as well.

Our research takes the three-dimensional log surface image and processes it to determine the location of the most severe external defects: overgrown knots, rotten knots, holes/gouges, and removed branches. These types of defects are usually associated with a significant surface rise or depression depending on the defect type. The image is processed using a robust statistical approach to generate a height map of the log. Defects are characterized and located by a height change from the surrounding log area. Many internal aspects of the defect can be predicted. This system is currently under development and is expected to permit an automated approach to determining interior defect information that is faster and less expensive than other internal detection methods.

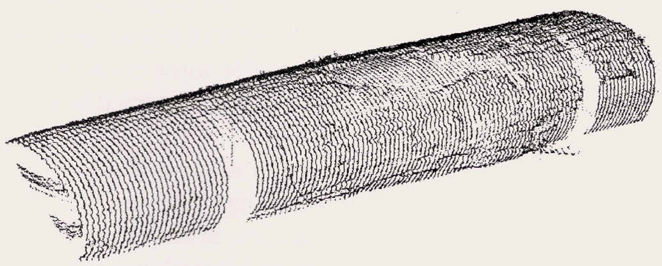

**Figure 1.**—*Sample scanned log in dot cloud format from scanner used in 2001.*

## Log Scanning

In the fall of 2001 we borrowed a portable, industrial log laser scanner from a sawmill optimization company. Using this scanner, a total of 162 yellow-poplar and red oak logs were scanned. This equipment scanned a laser-line around the log every 0.8 in. along the length. The average distance between points in each cross section is 0.04 in. A sample of the data scanned by this system is shown in **Figure 1** in dot-cloud format. The resolution of this data was sufficient to allow development of methods to detect severe defects based on a contour analysis approach (Thomas et al. 2006).

The log data from the scanner presented several problems. The data contained large areas of missing data which were shadows from the log supports (**Fig. 1**). In addition, the supports themselves appeared in the scans. Dangling bark, outliers, and other data issues complicated processing of the laser range data (**Fig. 2**). To process the data and detect defects, the three-dimensional log surface data was converted to two-dimensional im-

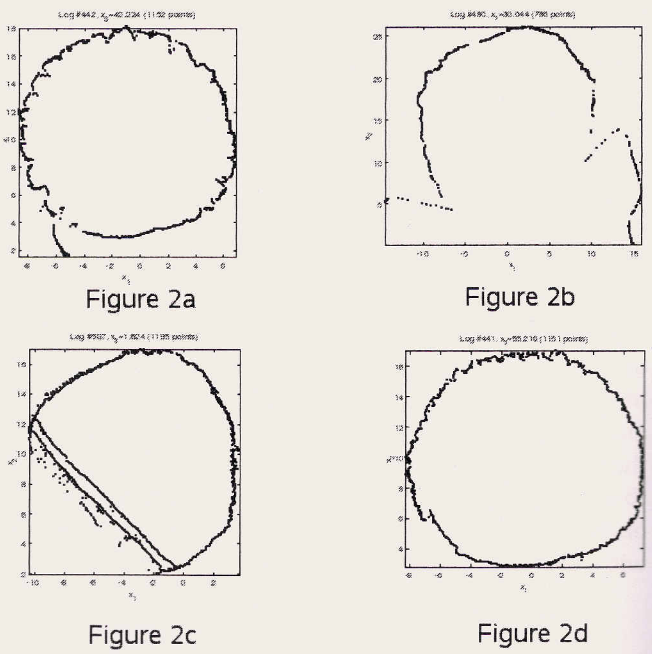


**Figure 2.**—*Various formations of outliers present in the cross-section data from laser scanning: (a) loose bark flakes in lower left corner, (b) outliers in form of scanning support structure and missing data due to structure, (c) outliers and shape of log at one end where the log was cut diagonally instead of squarely, and (d) a good log data cross section containing no outliers.*

**Figure 3.**—*Radial residuals generated by the log unrolling process presented as a grayscale image. Light pixels represent protrusions from the log surface, and dark pixels represent depressions. This log is approximately 9 ft in length with a diameter of 2 ft. The Z dimension is along the log's length. The θ dimension is around the circumference of the log.*

ages for processing (**Fig. 3**). To accomplish this we imposed a reference surface on the log data. Since logs are natural objects that are approximately circular or elliptical in cross section, we fit circles or ellipses to the log data to form the reference surface. Defects that correspond to rises or depressions on the log surface can be detected using contour levels estimated from the orthogonal distances between the reference surface and any point of the cross section.

Fitting quadratic curves (i.e., circles, ellipses) to two-dimensional data points is a nonlinear regression problem (Gander et al. 1994). Classic least-squares fitting methods failed because the laser log cross-sectional data contain missing data and/or large deviant data points. In robust statistics, outliers are defined as data points that strongly deviate from the pattern formed by the majority of the measurements. The laser data sets include outliers of the sort shown in **Figures 2a, 2b, and 2c**. To overcome the non-robustness of the least-square fitting, we resorted to the theories and methods of robust statistics (Hampel et al. 1986). The nonlinear form of the circle equation prompted us to develop a new robust estimation method that is an outgrowth of the one proposed by Mili et al. (1996).

Our nonlinear regression circle-fitting estimator is a generalized M-Estimator, termed GM-estimator (Thomas et al. 2004). It not only filters the errors in the measurements but also the errors in the circle model that are applied to a given cross-sectional data set. For a log sample with 120 cross sections, an equal number of circles are fitted, forming a reference surface for the residual extraction. Unlike the method described in Mili et al. (1996), our estimator minimizes an objective function that uses a weight function that levels off for large scaled radial distance between the associated data point and the fitted circle; it does this at every step of the iterative algorithm that solves the estimator. We tested the robustness of our estimator on real log data samples and found that the resulting fitted circles vary little among neighboring cross sections, yielding a smooth fit over the entire data of a log.

Due to the presence of extreme outliers and missing data in the laser log data, robust estimation techniques are well suited to this application. The developed programs can process an entire log-data sample by transforming the original log data set, which may contain a large number of missing and/or severely deviant data, into a sharper and cleaner image. The quality of the resulting grayscale image lays a solid foundation for the remaining defect-detection process. Contour levels derived from the residuals allow us to detect and further narrow the potential defect areas.

## Log Defect Detection

Defect detection begins after the three-dimensional data is converted to a two-dimensional surface. There are countless possible defect sizes, heights, shape, and type combinations – all of which greatly complicate the detection process. Our solution to defect detection was the implementation of an expert system (Thomas et al. 2007). Expert knowledge and expertise are applied in a stepwise fashion to rule out areas as defects, including areas in sizes smaller than a given threshold, nested in other curves, or long and narrow as determined by the "actual" width-to-length ratio (referred to as w/l for short). By "actual" we refer to the width-to-length ratio acquired through the calculation of the statistical medium of the widths of the area enclosed in the selected contour curve.

Log-surface defects come in many types, sizes, and shapes: knots, bumps or bulges, circular distortions, surface rise, and splits to name a few. Knots include overgrown, adventitious, sound, or unsound (rotten). Knots can occur in clusters of various numbers and sizes. Distortions can be heavy, medium, or light and usually indicate a knot that is completely encapsulated within the log. When data was collected for the expert system, we learned that approximately 60 percent of the severe defect types, including overgrown knots, rotten knots, bumps, sawn off or removed branches, splits, and holes have a height change, either a protrusion or a depression, of at least 0.5 in. when compared to the neighboring bark area. Some defects are easily identified by color or height characteristics, while others are not obvious except for their breaking of the natural bark pattern or texture. In log processing, some types of defects, such as knots and heavy distortions, are considered to be severe. Light distortions and adventitious buds are not as serious (the internal characteristics of these defects cause lesser grade and value loss).

Many severe defects are associated with a localized height change, thus a height analysis of the residual image provides information about the presence of such severe defects. A substantial, localized, and abrupt surface rise or depression greater than 1.0 in. is almost always a defect. The data resolution (0.8 in. per cross section) and the nature of external defect shapes restrict search scope in the algorithm. Because of this, we chose 3 in. as the lower threshold for defect diameter. If a defect was 3 in. or greater in diameter, this gave us three laser-scan cross section lines through the defect, a minimum needed for dependable detection. In addition, most severe defects are larger than 3 in. in diameter. Since the pixel values in the grayscale image represent radial distances between the fitted circle and the log surface, the analysis is straight forward. In the contour plot image, it is possible to discern the areas containing likely defects based on height information alone.

The algorithm attempts to find the most obvious defects based on their external characteristics, such as surface protrusion, width-length ratio thresholds, and area. These defects have a relatively significant height change (≥ 0.5 in.), and/or a relatively significant diameter (≥ 3 in.) and are expected to be detected by the search algorithm. Other, smaller defects (< 3 in. in diameter) are not expected to be detected by our current methods. Using the grayscale image shown in **Figure 3**, the algorithm generates a contour plot as depicted in **Figure 4** and determines the rectangles enclosing areas with a contour curve at the highest level. Then, some areas are selected if they are big enough or with a significant height. In **Figure 4**, four out of the nine surface defects are found using this method. **Figure 4** also shows a manually recorded map of the defects on the same log. The defect types detected by our scan-based algorithm shown in the contour map include SKCs (sound knot clusters), SKs (sound knots), and OKs (overgrown knots). Minor defects we did not expect to be able to detect include AKs (adventitious knots), AKCs (adventitious knot clusters), LDs (light distortions), and MDs (medium distortions).

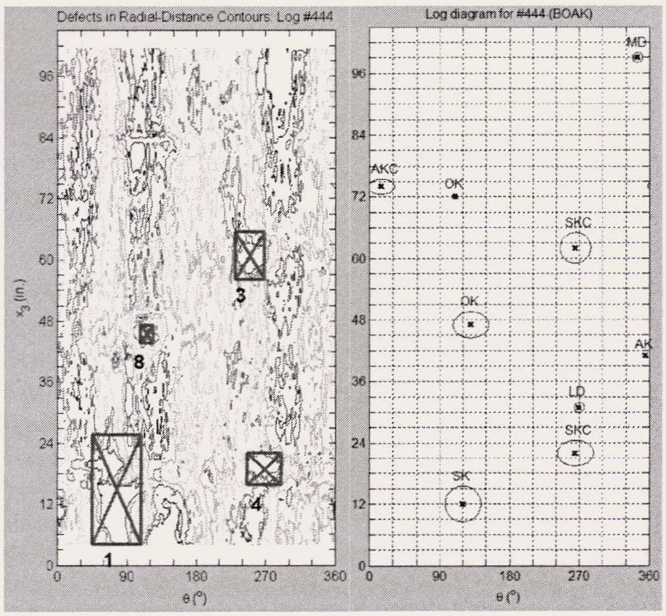


**Figure 4.**—*Contour plot of a log surface with the four most obvious defect areas marked with crossed rectangles labeled in the descending order of area size (left). Defect diagram illustrating the "ground truth" (right). Note that only five small and/or flat defects were not detected. Both plots were automatically generated by our Matlab programs.*

The current version of our system uses the contour image generated from the radial distances that provide a map of defect height change against the surrounding bark. **Table 1** presents statistics for the simulations of our defect detection system. Fifteen log samples were randomly chosen containing 162 surface defects in total. The detection system does not classify the type of defects (e.g., overgrown knots, unsound knots, sawn knots, etc.). Instead, defect classification is done manually through our examination of the detection results including the contour plots, the defect diagrams (ground truth), grayscale images, and the colored log photos. The last row of the table, excluding the value in the last column, displays the sums of the data in each column. The algorithm made a total of 72 defect predictions and has a probability of detection of 80 percent (47 of 59) for the most serious defect classes. In addition, it identified 11 of 103 defects, which, given their size characteristics, we

**Table 1.**—*Defect detection system results.*

| | Number of defects to be detected | | | | | | |
|---|---|---|---|---|---|---|---|
| | Expected | | Unexpected | | Grand total | | |
| Defect type | Total | Detected | Total | Detected | Total | Detected | False |
| Overgrown/unsound knots | 32 | 27 | 34 | 6 | 66 | 33 | |
| Sawn knots | 19 | 19 | 19 | 2 | 38 | 21 | |
| Others | 8 | 1 | 50 | 3 | 58 | 4 | |
| All types | 59 | 47 | 103 | 11 | 162 | 58 | 14 |

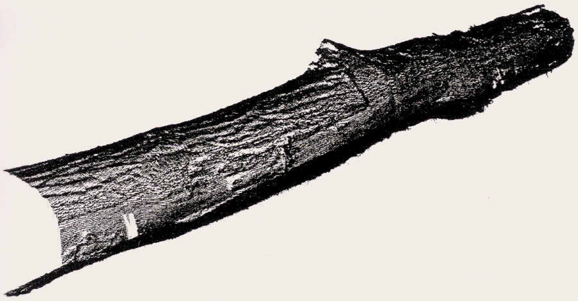

**Figure 5.**—*Laser scan of red oak log surface using scanner with 0.0625 distance between points.*

did not expect to locate. The algorithm also mis-identified 14 non-defective areas as defective on seven logs. The total area contained in the 14 false-positive detections was only 80 in.$^2$ (< 1 in.$^2$ each). Considering all of the defect classes, the detection algorithm has a 36 percent detection rate for all defects.

## Current and Future Work

The laser-log scanning system is effective in locating severe defect types. This external scanning system determines the diameter of the log at the defect and the width, length, and rise (if any) of the surface indicator. These variables are required input for the external/internal defect modeling system. The defect modeling system uses known strong correlations among external indicators and internal manifestations to predict internal defect features (Thomas 2007). We are working to combine the two systems to provide an external whole log scanner that infers knowledge of internal defect structures based on external indicators.

The resolution of the log scanner used in this study limited the size and types of defects that could be accurately detected. With the 3-in. minimum defect diameter for detection, the system had only three to four laser scan lines for that size defect. This equated to six to eight points of reference used to detect the defect – a difficult task. To solve these problems we constructed a high-resolution log scanner. The scanner was constructed using standard industrial laser-profile scanning components and custom software. This system scans along the log length in 0.0625 (1/16) in. resolution compared to 0.8 in. of the system used for this initial "proof of concept" study. A sample of the data obtained (in dot cloud form) from the scanner is shown in **Figure 5**. From this figure it can be seen that the resolution of the current scanner is much higher than that of the scanner used previously (**Fig. 1**). At the time of this writing, the scanning of a new high resolution log sample has just been completed. The modification and testing of the defect detection algorithms on the new sample has not been completed. But, it is expected that detection accuracy will improve and smaller sized defects (in the 1- to 2-in. diameter range) will be detectable.

It is expected that the resolution of this scanner will allow us to develop texture-based approaches to finding those defects that do not have a significant surface rise. In addition, we may be able to correlate aspects of the surface texture with internal features, thereby improving the predictive power of the internal defect prediction model for less severe defects.

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