DEFECT DETECTION ON HARDWOOD LOGS USING HIGH RESOLUTION THREE-DIMENSIONAL LASER SCAN DATA

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ABSTRACT

The location, type, and severity of external defects on hardwood logs and skills are the primary indicators of overall log quality and value. External defects provide hints about the internal log characteristics. Defect data would improve the sawyer's ability to process logs such that a higher valued product (lumber) is generated. Using a high-resolution laser log scanner, we scanned and digitally photographed 162 red-oak and yellow-poplar logs. By means of a new robust estimator that performs circle fitting, a residual image is extracted from laser scan data that are corrupted by extreme outliers induced by the scanning equipment and loose bark. The residuals provide information to identify defects with height differentiation from the log surface. Combining simple shape definition rules with the height map allows most severe defects to be detected by determining the contour levels of a residual image. In addition, bark texture changes can be examined such that defects not associated with a height change might be detected.

1. INTRODUCTION

Over the last few decades, a broad variety of scanning technologies have emerged for wood processing. Several scanning and optimization systems are on the market that aid in the sawing of logs into lumber. Among them are the defect detection and classification systems of logs and stems. Defect detection on hardwood trees and logs can be categorized into two areas: internal and external detection, to determine defects inside logs and on a log's surface, respectively. Currently, most available scanning systems are external models that use a laser-line scanner to collect rough log profile information. These systems were typically developed for softwood (pine, spruce, fir) log processing and for gathering information about external log characteristics [I]. Optimization systems then use this profile information to

better position the log on the carriage and improve the sawyer's decision-making ability. Adding external defect information to the optimization process is a natural extension of current technology.

Our research focuses on determining a method of locating external defects on log surfaces. To accomplish this we employed a commercially available TriCam scanning system with four laser units [2], which generated high-resolution profile images of the log surface in three dimensions. Such an image is then processed to determine the location of the most severe defects: overgrown knots, rotten knots, holes/gouges, and removed branches. These types of defects usually are associated with a significant surface rise or depression depending on the defect type. The image is processed using a new robust statistical method to fit a series of circles to the log data. By analyzing the radial residuals, defects characterized by a height change from the surrounding log area can be located.

More specifically, a typical log size is 10 to 20 inches in diameter and 8 to 16 feet long. Resolution of the scanned data is about 0.04×0.78 in^2 per data point. Typically, each line of log data can be approximated by a closed curve resembling a circle or an ellipse. Hence, one of the problems that we are dealing with is to fit a quadratic curve or surface to the recorded log data. It turns out that these data are corrupted by gross errors as bark on logs often becomes loose, forming flakes. Furthermore, the supporting structure underneath the log blocks the scanner, causes missing data. and tile shape of the structure can be seen in the scanned images. Statistically, measurements with large errors, known as outliers, can be regarded as observations that deviate from the pattern formed by the majority of the data set. Consequently, classical estimators based on the least-squares method cannot be used here to carry out curve or surface fitting because they generate incorrect estimates in the presence of outliers. We need instead to resort to robust statistics as initiated by Huber [3] and further developed by

Hampel et al. [4]. Based on this theoretical framework, we developed a new generalized M-estimator to fit circles to log data, which is able to downweight all types of outliers, hence bounding their influence on the estimates. These fitted circles allow us to extract residuals, determine contour levels, and finally detect and identity log defects. Let us stress that the contour levels revealed themselves as a powerful tool /or shaping the topology of the log surface and thereby, allowing us to pinpoint any atypical elevation or depression on the log surface by means of appropriate statistical methods. As a future work, pattern recognition methods will be carried out for defect identification and classification once the taxonomy of the defects has been completed.

The paper is organized as follows. Section 2 describes the robust fitting procedures for estimating log shape. Section 3 characterizes several severe external defects on hardwood logs. Section 4 presents examples of results that we have obtained to illustrate the potential of this approach in detecting surface defects. Finally Section 5 contains concluding remarks and future work.

2. LOG IMAGE PROCESSING

Severe external defects that correspond to rises or depressions on the log surface can be observed from the three-dimensional log surface image. This suggests that we may extract the height change on the log surface from its 3-D image to determine the defect location. We apply robust statistics techniques to fit quadratic curves to cross sections in the presence of a high noise level in the log data, and a new generalized M-estimator was developed. Orthogonal distances between fitted curves and the log surface data, or radial residuals, are estimated, which reflects height change from the surrounding log area. Detects characterized by surface rises or depressions could thus be located.

2.1. Circle Fitting and Outlier Suppression

Since logs are natural objects that are approximately circular or elliptical along the cross sections, we experimented with fitting circles and ellipses to the log data, which all together limn a reference surface, or virtual log, needed for defect detection. 2-D quadratic curve fitting is a problem in nonlinear regression [5]. One of the main problems that we had to overcome is the presence of extreme outliers and missing data in the log data cross-sections. See Fig. 1 for such an example. Missing data are due to the blockage of the log by the supporting structure while extreme outliers are irrelevant data caused by both dangling loose bark and the scanning system, duplicate data generated by scanner calibration errors and unwanted data from the supporting

structure under the log. As evidenced from Fig. I, the classical least-squares estimator failed to provide a good fit from such corrupted data set. Obviously, a robust estimator that suppresses the outliers is needed here.

The nonlinear form of the circle equation prompted ns to develop a new robust estimation method that is an outgrowth of the one proposed by Mili et al. [6]. It is a generalized M-estimator (GM-estimator) that fits a nonlinear regression model of the circle given by

$$(x_1+p_1+\eta_1)^2+(x_2+p_2+\eta_2)^2+p_3^2+e=0, \qquad (1)$$

where $\underline{p} = [p_1, p_2, p_3]^\top$ is the parameter vector containing the center coordinates (p_1, p_2) and the radius p_3 of the circle and where $\underline{x}=[x_1, x_2]^T$ is the two-dimensional measurement vector containing the data in a cross section from the scanner. The robustness of this GM-estimator stems from the tact that it not only bounds the influence of the model errors, e, hut also of the errors in measurements, $\underline{\eta}=[\eta_1, \eta_2]^r$. This is achieved by minimizing an objective function expressed as

$$J(\underline{p}) = \sum_{i=1}^{m} w_i^2 \, \rho(\frac{r_i}{s_i w_i}), \qquad (2)$$

where

$$\rho(\frac{r_i}{\sigma_i w_i}) = \begin{cases} \dfrac{1}{2}(\dfrac{r_i}{s_i w_i})^2 & \text{for } \left|\dfrac{r_i}{s_i w_i}\right| \le \lambda \\[2ex] \lambda\left|\dfrac{r_i}{s_i w_i}\right| - \dfrac{\lambda^2}{2} & \text{for } \left|\dfrac{r_i}{s_i w_i}\right| > \lambda \end{cases} \qquad (3)$$
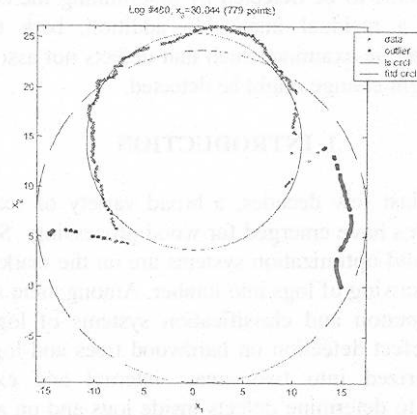

Figure 1 – A log data cross-section with outliers marked and with a fitted circle obtained by means of the new robust GM- estimator displayed in continuous line. Shown also is the least squares fit in dashed line.

Table 1 - Some statistics of the measurements and calculated feature values of three defect types: overgrown knots (OK), sound knots (SK), and unsound knots (UK).

Type	Width (in.)	Length (in.)	Surface rise (in.)	Surface Dep.	Curvature along w.	Curvature along l.
OK	4.5-5.5-6.5	5.5-6.5-7.5	1.0-1.5-1.5		0.25-0.33-0.4	0.17-0.22-0.28
SK	4.6-6.5-8.9	6.6-9.5-124	0.6- 1.0-1.5	0.8- 1.0-1.3	0.11-0.16-0.33	0.06-0.09-0.16
UK	5.5-6.0-7.0	6.3-7.5-9.5	0.9-1.0-1.5	0.9-l.0-l.5	0.19-0.22-0.18	0.13-0.16-0.19

In the forgoing equations, $p(,)$ is the Huber function, s_i is the median of $|r_i|$ times a correction factor of 1.4826 for Fisher consistency, and λ is a threshold fixed to 1.5. Concerning the function w_i it is a weight function that decreases asymptotically from one to zero as the relative size of the radial vector $\underline{d}_i$ between the point $\underline{x}_i$ and the fitted circle gets larger than a given statistical threshold. It is this weight function that makes the estimator robust to large errors in the measurements, $\underline{\eta}$. Indeed, we observe from (2) and (3) that when the absolute value of a standardized residual, $r_i(s_i\,w_i)$, is smaller than λ, the objective function J$(\underline{p})$ given by (2) is that of the leastsquares estimator (L$_2$-norm estimator), otherwise it is that of an L$_1$-norm estimator. In the latter case, the data point is downweighted. Note that the weight function w_i takes small values for outliers (much smaller than 1), forcing the objective function to switch from an L$_2$- to an L$_1$-norm criterion, and hence, bounding their inl1uence on the estimates.

2.2, Generating the Residual Image

The next step is converting the 3-D Cartesian coordinates into a 256 gray-level image (Fig. 2). In this process, the log surface is unrolled onto a 2-D coordinate space. In essence, this process creates a "skin" of the log surface representing the pattern of the logs' bark along with the humps and bulges associated with most defects. Using the adjusted, fitted circle for each cross section, we calculate the residuals (distances between circle and log surface points), which are scaled to range from 0 to 255 gray scales. To save space and future processing time, the resolution of the output gray-level image from log-data unrolling is reduced. The Gaussian pyramid algorithm [7] is applied and a 5x5 window is used to smooth and subsample the image. The image is reduced to 25 percent of the original size, i.e., roughly 500 KB/image. This speeds additional analyses of the image with little or no loss of data of interest.

2.3. Robustness and Ellipse Fitting

To prove that our nonlinear circle-fitting GM-Estimator is robust against outliers, we derived its ini1uence function, which reflects an estimator's robustness [4]. It was shown

that this influence function is bounded for both types of errors, namely the model errors and the measurement errors. Thus, our circle-fitting estimator is robust against extreme outliers of both kinds.

We also experimented with our new robust GM-Estimator to fit a linear model of the ellipses while incorporating the heteroscedastic errors in measurements [8]. The advantage of ellipse fitting is that it provides more detailed results. However, it is not as easy since there are more parameters involved in the model.
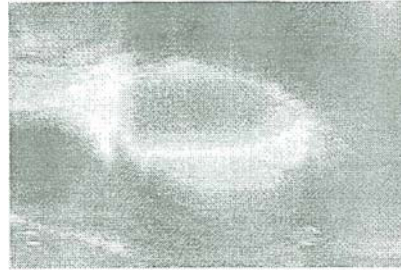

Figure 2 - A portion of a gray-scale residual image showing a large sound knot detect in the center.

3. EXTERNAL DEFECT CHARACTERISTICS

To provide distinct feature data that separate external defect classes in robust cluster analysis, We measured and photographed about 200 medium to severe red-oak and yellow-poplar defect samples. Our goal is to better define and characterize external defect types of hardwood species from the conventional forest industry perspective; to extract features unique to each detect type; and to categorize external defect types discernible by using the 3-D laser data. Figure 3 contains two photographs of a defect, and Table 1 lists statistics of the measurements and calculated feature values of three defect types.
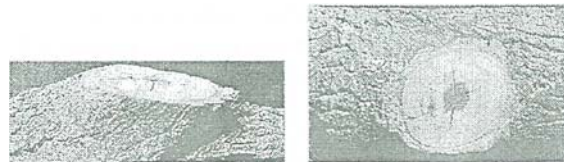

Figure 3 - Side and top views of a sound knot defect.

4. SIMULATION RESULTS

Using the gray-level image, shown in Figure 2, we can generate a contour plot (fig. 4), where it is possible to discern the areas containing likely defects based on height information alone. We developed an algorithm to generate rectangles that enclose areas with contour curves at the highest level. The areas are selected depending on their sizes. Our simulation showed that the majority of the most protruding or depressing detects with a diameter at least 3.5 inches is largely detected. However, the rectangles as in Fig. 4 often enclose a portion, e.g., a comer, of the external defect. Further analysis is required to correctly map the exact defect area.

Figure 4 - A portion of a contour plot generated from the gray-scale residual image in Figure 2. The warmer the color, the higher level the contour. The rectangle frames the highest contour which encloses the defect.

Defects with little surface variation are not covered in the highest or lowest contour curves and thus cannot be enclosed in the rectangles. Such defects include small overgrown knots and sound knots, and severe or medium distortions. In general these are less severe than big knots or deep cracks all log surface.

5. CONCLUSION AND FUTURE WORK

This paper describes our approach to detecting surt1ice defects in hardwood logs. Robust estimation and filtering techniques are well suited to this application. The current programs can process an entire log-data sample that may contain large amounts of missing data and severe abnormal data (outliers) due to the nature of data collection. The robust methods and procedures in these programs apply common heuristics to remove outliers. The original log data are processed and transformed into a sharper and cleaner representation of the entire log. The quality of the gray-level image lays a solid foundation for the remaining defect-detection process. Contour levels of the residuals make it possible for further narrowing down the potential defect areas.

We may analyze residual images generated from circle-, ellipse, and cylinder- fitting methods and combine the results to help better identify detects. Compared to circle fitting, the resulting residual images from ellipse fitting, however detailed, are noisier. Cylinder fit1ing gives a coarse hut smooth picture; circle fitting provides more details, but introduces certain types of noise; and ellipse-fitting presents the most-detailed residual image, however noise level is the highest as well.

The generation and initial processing of the residual image is not the final step of this work. At this point, only log unrolling and height analyses methods have been examined. Currently we are developing an algorithm that determines whether an area of interest contains a sawn knot, by locating the approximately straight line segment in a cross-section. Texture analysis methods win also be investigated to detect defects without a significant height change, which are not detected using the contour method. Further, a preliminary study was conducted to extract features of external defect types from randomly chosen defect samples. These features will be used to train a robust clustering and classification system for the defect classification.

6. REFERENCES

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