Wane Detection on Rough Lumber Using Surface Approximation

Sang-Mook Lee[a], A. Lynn Abbott[b], Daniel L. Schmoldt[c]

[a]*Bradley Department of Electrical and Computer Engineering, Virginia Tech, Blacksburg, VA 24061 USA, lsmook@vt.edu*
[b]*Bradley Department of Electrical and Computer Engineering, Virginia Tech, Blacksburg, VA 24061 USA, abbott@vt.edu*
[c]*USDA Forest Service, Biological Systems Engineering Dept., 460 Henry Mall, University of Wisconsin, Madison, WI 53706 USA, dlschmol@facstaff.wisc.edu*

Abstract

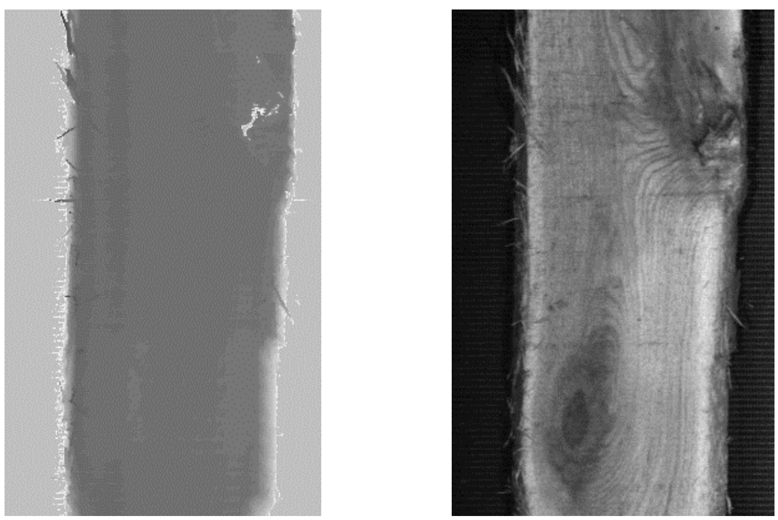
The initial breakdown of hardwood logs into lumber produces boards with rough surfaces. These boards contain wane (missing wood due to the curved log exterior) that is removed by edge and trim cuts prior to sale. Because hardwood lumber value is determined using a combination of board size and quality, knowledge of wane position and defects is essential for selecting cuts that maximize profit. We have developed a system that uses a structured-light system to obtain profile (thickness) images of unplaned boards, in addition to gray-scale images for defect detection. The focus of this paper is to describe a new approach for detecting wane boundaries through the analysis of these profile images. The problem is difficult because bark and other debris adversely affect the laser-based imaging process, and because variations in surface reflectance also cause inaccuracies in the resulting images. The problem is compounded by the need to perform wane detection rapidly in a manufacturing environment. The method that we have developed relies on a combination of column-wise image statistics, selective smoothing, and the analysis of surface shape. Initial wane edge estimates that are obtained using the smoothed image are then refined by analysis of the original image data. Based on visual assessment, the current method appears to improve dramatically on traditional thresholding techniques.

Keywords: Hardwood, Wane Detection, Surface Curvature

Introduction

In present-day hardwood sawmills, logs are first cut into boards that retain residual bark, called wane, and other undesirable features of the log. Edger and trimmer operators then visually examine the surfaces of each board, and make quick judgments about the placement of cuts based on their knowledge of lumber grades and current lumber prices. Ideally, edge and trim cuts will be selected so that the sale value of each board is maximized. In practice, however, optimizing the value of each board in this manner is a complex decision that is difficult even for experienced operators. The decision is based on the position of wane and defects, as well as current market prices for wood.

This paper considers the problem of automatically detecting wane on rough (unplaned) hardwood lumber. Wane detection and analysis is one part of an automated scanning system for optimizing edging and trimming of hardwood lumber in sawmills. This capability, together with automatic defect detection, will form the nucleus of computer-driven edging and trimming. The analysis presented here is intended for use with a structured-light profiling system that is described in Lee, et al. (1999). As described in the next section of this paper, the scanning system captures *profile* images (or, equivalently, *range* images) in which each pixel represents a measurement of board thickness. As an example, a portion of a profile image is given in Figure 1.



(a) (b)

Figure 1. *Registered range and intensity images for a rough board. (a) Example range image, in which darker areas represent points on the board that are closer to the camera. (b) Corresponding intensity image.*

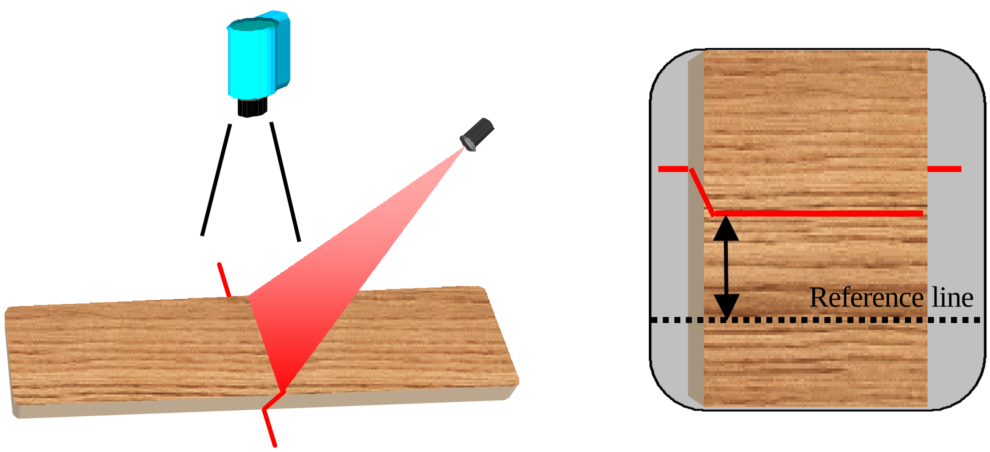
At first glance, the detection of wane would appear to be a relatively simple problem involving the selection of a threshold thickness value in the profile image. Although this approach might be adequate for planed lumber, the problem is much more difficult for unplaned lumber because images are typically contaminated by additional types of noise. Our approach to the detection of wane is to search for discontinuities in surface characteristics of the wood. Smoothing operations are employed to reduce the effects of noise.

After describing the imaging system, the section that follows presents additional details on the types of noise that are present. Additional sections describe our wane-detection method analytically, present experimental results, and provide concluding remarks.

Data acquisition

In a widely used technique known as sheet-of-light profile imaging (Figure 2), a plane of light is generated onto an uneven surface. Light that reflects from the surface appears as a 2-dimensional curve in an image, when viewed from an angle relative to the light plane. By using triangulation, it is possible to estimate thickness values over the surface of the object. Because many lumber defects (e.g., voids, wane, twist, and splits) are associated with surface irregularities, profiling is extremely useful in wood applications. In addition, it is possible to obtain intensity information simultaneously that is exactly correlated spatially with profile information.

In our prototype system, the profile laser is mounted at an angle of 45 relative to the direction of travel of the board. A digital camera is mounted vertically above the board, and can provide images for estimating board thickness. The digital camera that is used in this system is the MAPP 2200 "smart camera," developed by Forchheimer, et al. (1992), and also described in Åstrand (1996). The unit captures images of 256 rows by 256 columns. Unlike conventional cameras, the internal MAPP (matrix array picture processor) sensor contains an on-board processor that is capable of manipulating complete rows of this array, in both digital and analog forms.

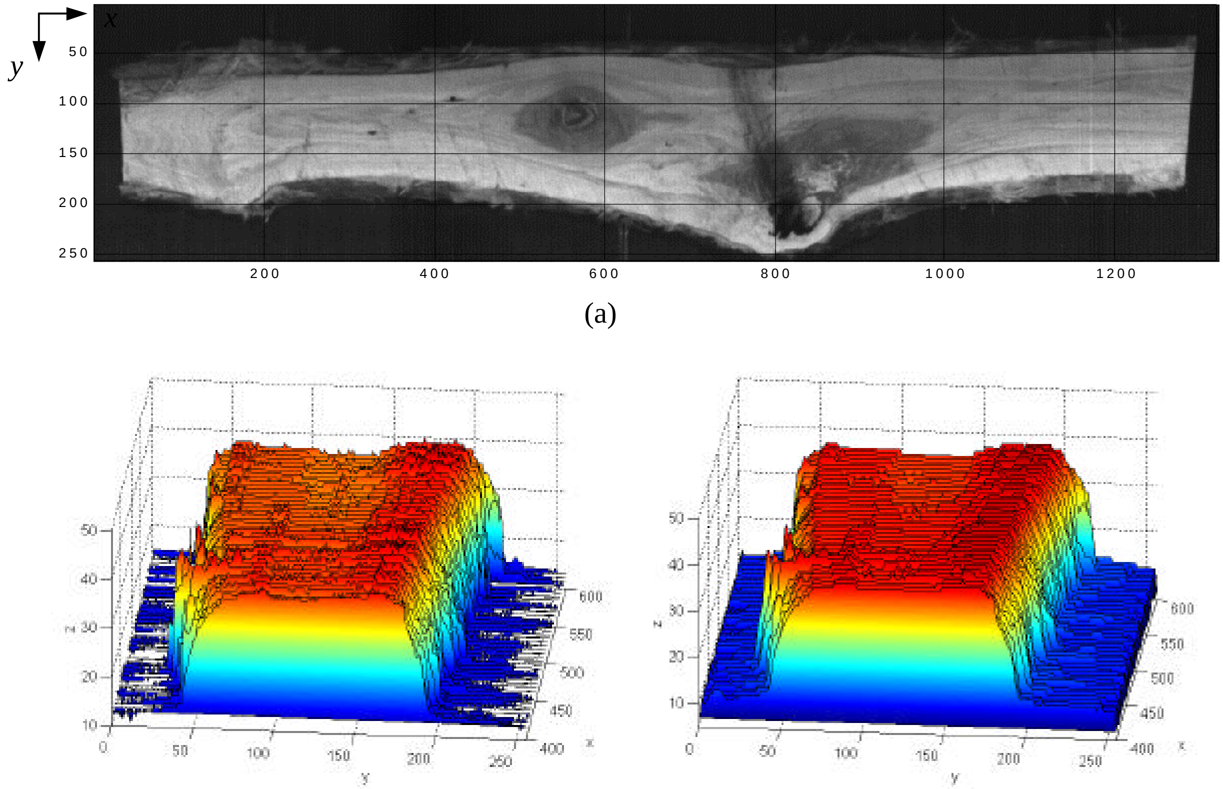


(a) (b)

Figure 2. *Profile imaging geometry. (a) A camera is mounted vertically, looking downward at a board. A laser source generates a plane of light that is 45 degrees relative to the horizontal. (b) From the camera's point of view, different board thicknesses cause the laser light to appear as a 2-dimensional curve in an image. Deviation of the light from a known location is directly related to the thickness of the board.*

Noise effects

A profile image of a rough hardwood board suffers from various noise sources: noise from residual bark, debris, and dust; spatial quantization of the sensor array; sampling and quantization of intensity values; thermal sensor noise; and problems in thickness estimation due to variations in surface reflectance. Figure 3 shows the effects of various noise sources. The profile plot depicts a portion of the board. Residual bark and debris contained in the wane area make it difficult to detect wane boundaries with high accuracy. Unlike other noise sources, which can be addressed in many cases by applying smoothing filters, residual bark and debris are still prominent in the smoothed profile image (lower left corner in Figure 3b and 3c). In fact, because no smoothing filter can perfectly remove noise due to bark and debris from the wane area, this presents the most challenging part of the wane detection problem using profile images. We can also see the reflectance variation effect by comparing the left and right side of the board in Figure 3c. In the tracheid image (Figure 3a), the lower part of the board is generally brighter than the upper side, producing an uneven profile image.



(b) (c)

Figure 3. *Example of noise effects. (a) Tracheid (reflectance) image of an unplaned board. (b) A portion of the profile image for this board. Only columns 400 to 600 are shown. (c) Smoothed version of profile image.*

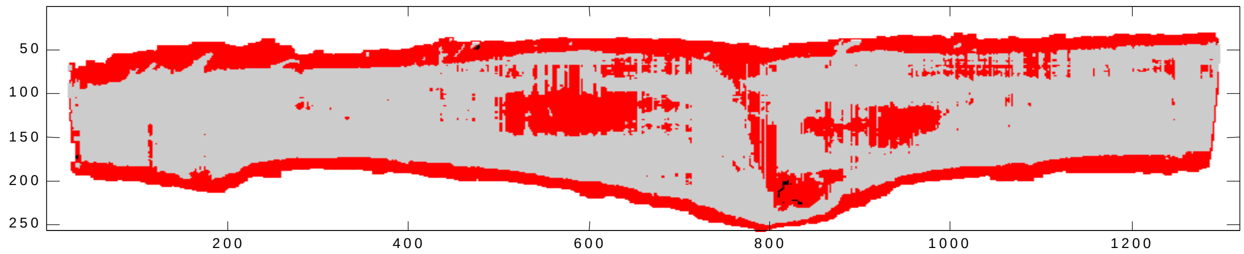
Wane detection

Threshold methods

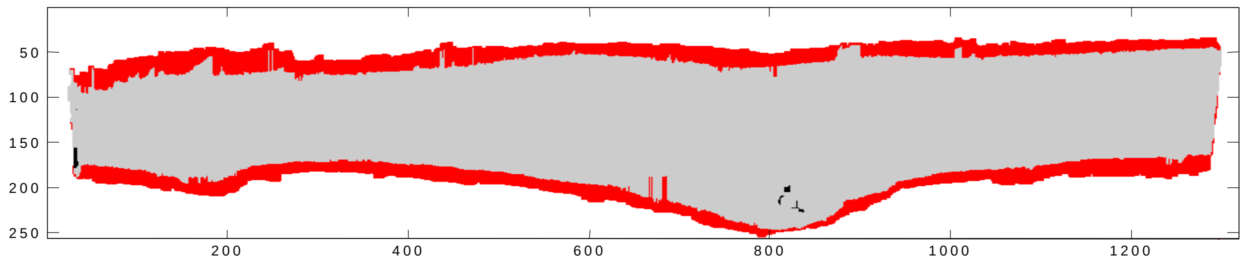
Simple threshold methods fail for most boards tested due to the noise described above. For example, Figure 4a illustrates the case where a single threshold is computed for column *x* of the profile image using

$$T(x) = m(x) - s(x) \ , \qquad (1)$$

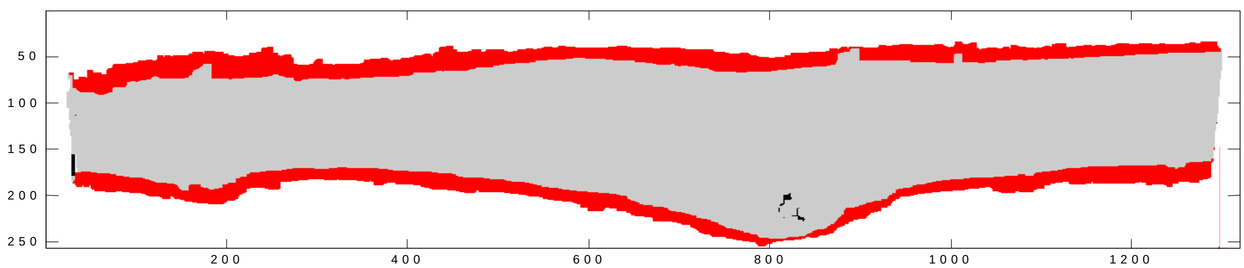
where $\mu(x)$ and $s(x)$ are the mean value and standard deviation, respectively, for a given column. Any pixel in the profile having a value less than $T(x)$ is declared to be a wane point. This method has several shortcomings, however, as indicated by the many incorrect wane regions shown in Figure 4a. Debris or defects often elevate the threshold value above the clear-wood area of the board. Modifying equation (1), offseting the threshold by more than one standard deviation, is also unsatisfactory.



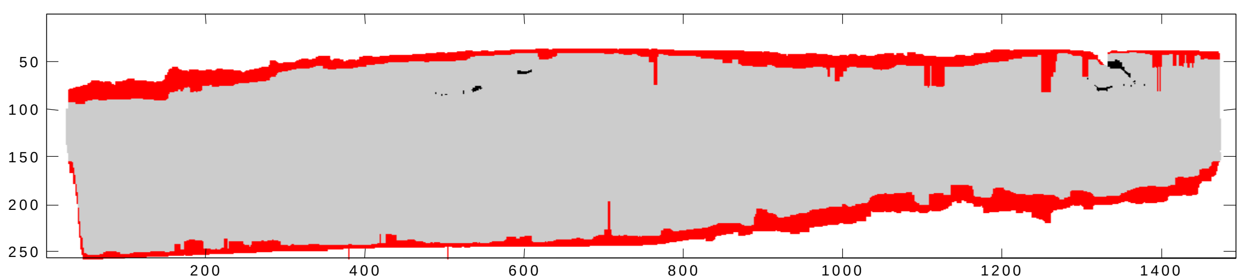
(a)



(b)



(c)



(d)

Figure 4. *Comparison of threshold methods for wane detection. (a) Simple threshold method (column-by-column processing), which fails in most cases. The threshold value is based on thickness statistics for each column. (b) Refined threshold method. (c) Further refinement. A median filter is applied to the wane edge positions on the previous image to obtain smoother wane contours. This final result is very good. (d) Example for a different board, with poor results. Unfortunately, the selection of thresholds using statistical criteria has not resulted in a wane-detection method that is robust over many boards.*

Because of these problems, we considered a somewhat more sophisticated method for selecting a threshold. In this case, a threshold value for the upper (or lower) half of column x is determined by

$$T(x) = \min(T_1(x), T_2(x) - q) \tag{2}$$

where T_1 is a threshold value selected at one standard deviation below the mean thickness value for this (half) column, and T_2 is another threshold value that corresponds to the mode (the highest peak) of the histogram ($h(x)$) for that column, and q is a constant selected empirically in the range $0 < q \le 1$. That is,

$$T_1(x) = m(x) - s(x) \tag{3}$$

$$T_2(x) = \arg\max(h(x)) \; . \tag{4}$$

As described above, when debris appears in the wane area, T_1 is often higher than the value of the board surface, and this yields incorrect results. However, in such a case, T_2 gives more a reasonable answer. Operator $\arg\max(\cdot)$ finds an index at which the function has maximum value. Figure 4b shows that the refined thresholding method successfully avoids most undesired effects of the various noise sources. A median filter is then applied along the wane-edge positions of Figure 4b to refine the wane contours (Figure 4c). This has the effect of smoothing the wane contour, removing most of the outliers.

Although this second method worked well for this example image, repeated trials with other boards failed to provide results that were completely satisfactory. An example of this is given in Figure 4d.

Surface normal and curvature estimation

Because of problems encountered in finding a suitable threshold, we began to develop a method for wane detection that depends on surface properties such as orientation and curvature. Although it is possible to estimate these properties using discrete differences, we adopted a surface-fitting approach that is more robust in the presence of noise. (See Hoffman et al., 1987, for additional discussion in the context of range data.)

Similar to the approach described in Besl et al. (1988), we model thickness as a function of two variables that is C^2-continuous, $z(x, y)$. The variables x and y correspond to the column and row directions of the profile image, respectively. A thickness value is estimated within a local 5×5 neighborhood ( ) of the data points using classical least -squares fitting of a biquadratic polynomial:

$$z(x, y) = ax^2 + bx + cy^2 + dy + exy + f \; . \tag{5}$$

This results in local values for the coefficients, a, b, c, d, e, and f to minimize the error criterion

$$E = \sum_{z_i \in \Omega} (z_i - \hat{z}_i)^2 , \tag{6}$$

where $z_i = z(x_i, y_i)$ is estimated analytical value and $\hat{z}_i$ is a corresponding measured thickness value.

Using this surface model, we proceed to determine surface orientation and curvature. These can be expressed using derivatives of z, and these derivatives are easily found using equation (5). The orientation of a surface is expressed in terms of the surface normal vector. The surface normal at a point $P = (x, y)$ is denoted by $\vec{n}_P$ (Carmo, 1976),

$$\vec{n}_P = (-p, -q, 1)^T \tag{7}$$

where (p, q) is the gradient at point P of the surface. That is, p and q are defined as

$$p = \frac{\partial z}{\partial x}, \quad q = \frac{\partial z}{\partial y}. \tag{8}$$

Therefore, we can explicitly write the surface normals with the estimated coefficients as follows:

$$\vec{n}_P = (-2ax - b - ey,\ -2cy - d - ex,\ 1)^T. \tag{9}$$

Surface curvature can be expressed in any direction within the tangent plane at a surface point. Let $\vec{r}_x$ and $\vec{r}_y$ represent any two different directions in the tangent plane. Then an arbitrary direction can be expressed as

$$l\vec{r}_x + h\vec{r}_y \tag{10}$$

and the surface curvature in this direction at point P is given by (Faugeras, 1993)

$$k(P) = \frac{l^2 z_{xx} + 2\,l\,hz_{xy} + h^2 z_{yy}}{n\left(l^2\left(1+z_x^2\right) + 2\,l\,hz_x z_y + h^2\left(1+z_y^2\right)\right)}\ , \tag{11}$$

where

$$\begin{aligned} n &= \sqrt{1+z_x^2+z_y^2} \\ z_x &= \frac{\partial z}{\partial x} = 2ax + b + ey, \quad z_y = \frac{\partial z}{\partial y} = 2cy + d + ex \\ z_{xx} &= \frac{\partial^2 z}{\partial x^2} = 2a, \quad z_{yy} = \frac{\partial^2 z}{\partial y^2} = 2c, \quad z_{xy} = \frac{\partial^2 z}{\partial x \partial y} = e \end{aligned} \tag{12}$$

In our application, because wane is oriented in the *x*-direction, we consider only the *y*-directional features by setting $l = 0$ and $h = 1$. The resulting curvature expression is

$$k_y(P) = \frac{z_{yy}}{n\left(1+z_y^2\right)} = \frac{z_{yy}}{\sqrt{1+z_x^2+z_y^2}\left(1+z_y^2\right)}\ . \tag{13}$$

Similarly, the y component of the surface normal is given by

$$n_y(P) = -q = -\frac{\partial z}{\partial y} = -(2cy + d + ex) \tag{14}$$

Search criteria

For each column of the image, the system searches for two wane boundaries (corresponding to the two edges of the board). In each case, the search begins at a point within the wane region and proceeds toward the interior of the board. The following heuristics are used in the search:

1. Near the wane boundary, the *y*-component of the surface normal should be small in magnitude. This corresponds to a small rate of change along the column of the image, and can be represented as follows, where a is an empirically chosen constant:

$$\left|n_y(P)\right| < a \tag{15}$$

2. Near the wane boundary, curvature in the y direction should be small in magnitude, with a value that is negative (or zero). The requirement for small magnitude eliminates sharp peaks and valleys from consideration, which typically are caused by debris or residual bark. The requirement for a negative value corresponds to a surface that more closely resembles a peak than a valley, as we expect for a wane boundary. This heuristic can be represented as follows, where b is also a constant:

$$b < k_y(P) \le 0 \tag{16}$$

Using only the first criterion, wane detection can fail when the surface patch is estimated at the top of the protruded part, as illustrated in Figure 5. The second, curvature-based criterion helps avoid such cases. Points satisfying both criteria are more representative of true wane edge positions.

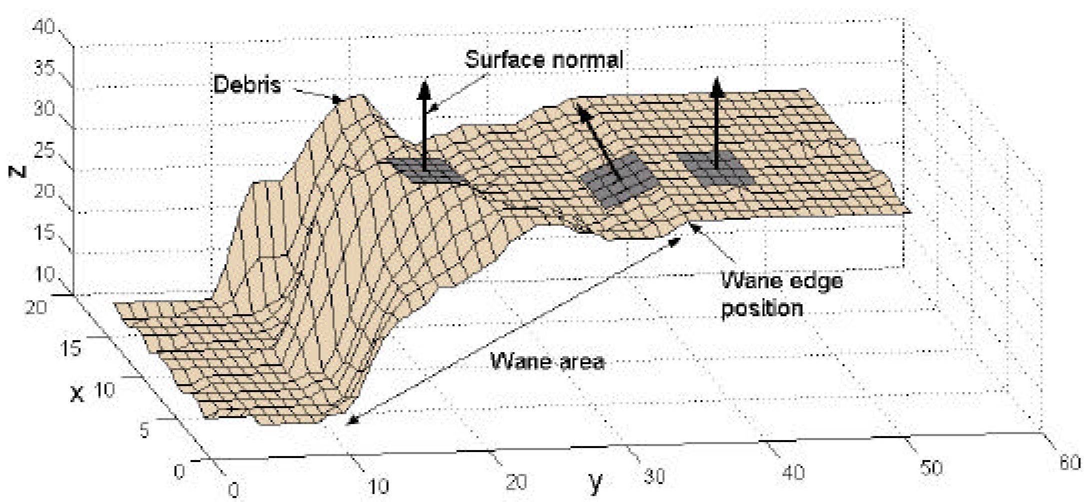


Figure 5. *Profile plot of several image columns. The wane region extends approximately from row 10 to row 40. Rows 0 to 10 represent background, and rows 40 and higher represent the sawn portion of the board. Detection of the wane boundary is made difficult because of the presence of bark and debris in the image.*

Adjustment

There is still a problem with this procedure, however. The smoothing of the profile image that occurs during preprocessing tends to displace the edge position by a small amount. To compensate for this, our algorithm searches the original image outward from the initial estimate of the wane boundary. In this case, a discrete approximation of the second derivative is computed, and the first zero-crossing point is selected as the wane-boundary position. The second derivative in the column direction can be expressed as follows,

$$\Delta_y^2 \hat{z} = \hat{z}(x, y-1) - 2\hat{z}(x, y) + \hat{z}(x, y+1), \tag{17}$$

where x and y now represent row and column locations in the image.

Further refinement

The method described above results in two wane-boundary positions per each column. However, because each column is processed independently, it is often the case that adjacent columns are not in strict agreement. As a post-processing step, we reduce these undesirable effects by filtering the wane-boundary curve. This can be done efficiently after scanning the whole board. Represent one wane boundary as

$$w = h(x) . \tag{18}$$

Then, the median operation

$$\tilde{w} = \underset{i-d \le j \le i+d}{median} \left(h\left(x_j \right) \right) \tag{19}$$

can be used to remove outliers. Here, $2d$+1 is the window size of the median filter.

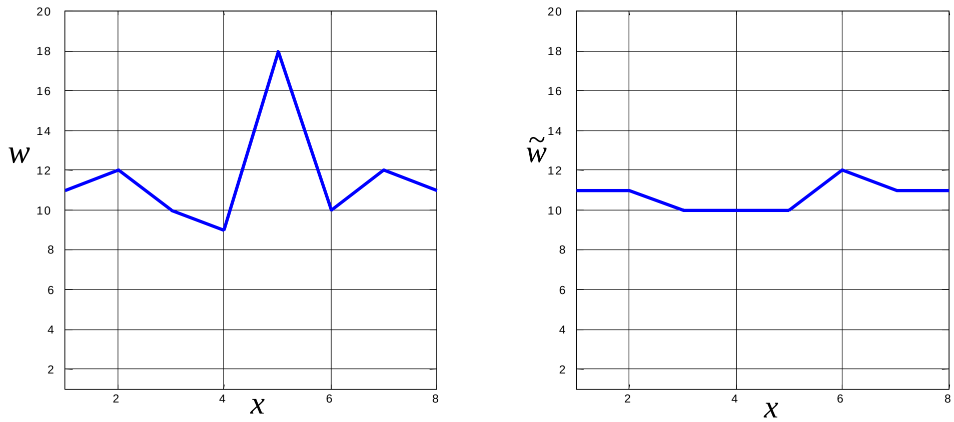


Figure 6. *Smoothing a wane boundary by median filtering. (a) Original data (8 points only) that contain an outlier at x=5. (b) Filtered version of the previous data. The outlier has been suppressed.*

Implementation and experimental results

We have tested the proposed method using profile data scanned with the prototype inspection system. Figure 7 shows a profile plot of one column. To reduce the noise level, we applied a 3×3 averaging filter during a preprocessing step. The solid line represents smoothed data and the dotted line is the original data. The method selects the first point that satisfies both criteria, working from a "start position" to the "1/3 position" (the point 1/3 of the board's width from the board edge). The upper start position is selected in the wane area by the procedure below (and the procedure for the lower wane area is similar):

1. For the upper side of column x, select the 1/3 position, $y = l$. We assume that this point does not lie in the wane region, and can therefore serve as a reference height for the interior portion of the board.
2. Check that l is not a point in a split or hole by confirming $\left|\operatorname{avg}_y(\hat{z}(x,y)) - \hat{z}(x,l)\right| < g$, for a suitable constant g. If this is not the case, select a valid point that is nearer to the board edge.
3. Find an intermediate position, L (dashed level in Figure 7). L is the minimum value y from the set $\left\{y \mid s < y < l \text{ and } \left|\hat{z}(x,y) - \hat{z}(x,l)\right| \le 2\right\}$, where s is the outside edge of the board. If there are splits or holes between the 1/3 position and the first point of the board, this step avoids points in splits or holes as possible start positions.
4. Select the start position (diamond mark in Figure 7) as the maximum value y from the set $\left\{y \mid s < y < L \text{ and } \left|\hat{z}(x,y) - \hat{z}(x,L)\right| \ge 2\right\}$.

Due to the smoothing effect, the estimated wane edge is pulled toward the inside of the board. The adjustment step successfully compensates for this bias by finding a true edge position on the original image.

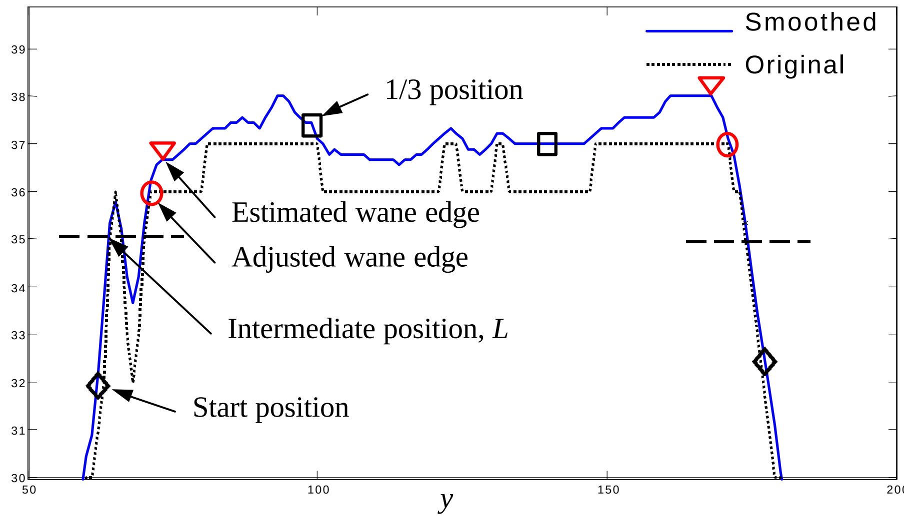


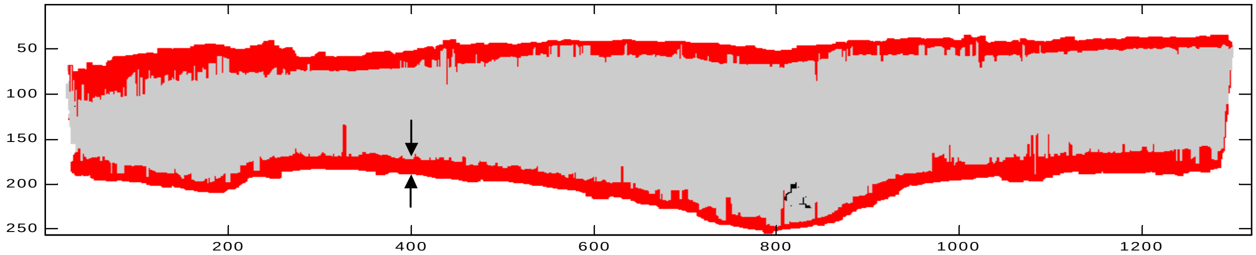
Figure 7. *Demonstration of the method using a profile plot for one column. The two ends of the column are processed separately. First, a point is carefully selected from the wane area (diamond mark). Second, a search is conducted toward the 1/3 position of the board (square mark) for a point that satisfies both search criteria. The triangle mark represents the wane edge that is found for this case. The adjustment step searches within a small neighborhood of the original data to find an improved wane edge (circle mark).*

Figure 8 displays results of the surface approximation method for a board. It shows that the adjustment step can eliminate many outliers as shown in (a) and (b). Notice that the estimated wane region in (a) is thicker than in (b) as noted by the markings at column 400. This is due to the smoothing effect. Figure 8c shows the final result after further refinement with median filtering along both wane edges. In Figure 9, we re-examine the failed case of the threshold method (Figure 4d) using the surface approximation method. Much cleaner and reasonable wane-boundary positions are detected.

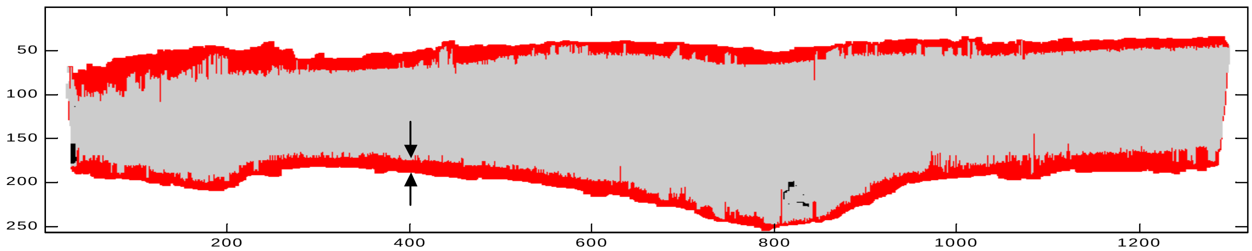
Conclusion

We have successfully implemented a surface approximation technique to detect wane in profile images of rough lumber. The images are contaminated by a significant amount of noise, including noise from residual bark and debris. The algorithm operates primarily on a column-by-column basis, using surface curvature and normal direction as search criteria. These criteria are used to identify crease edges that represent the boundary of wane regions. The surface normal alone will often find bark/debris protrusions as false creases, but the curvature feature helps avoid steeply curving regions that correspond to sharp peaks.

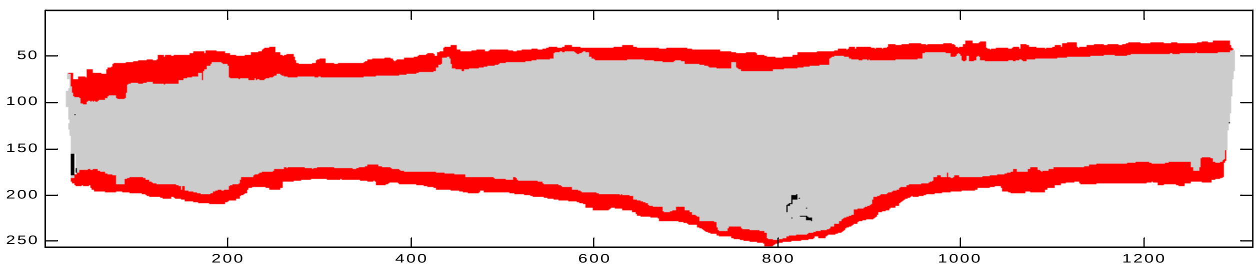
From some of the board profiles shown here (e.g., Figure 7), it is clear that the detection of wane edges can be difficult even for human observers. In practice, of course, humans use additional cues (such as color, grain direction, recognition of surface characteristics, etc.) to detect wane. For fast processing in automated systems, however, thickness measures resulting from laser profiling appear to be the best sources of data for detecting wane, and for identifying other wood-deficit defects, such as holes and cracks.



(a)



(b)



(c)

Figure 8. *Surface approximation method (a) without adjustment and (b) with adjustment. (c) Results of median filtering of (b) along both wane edges.*

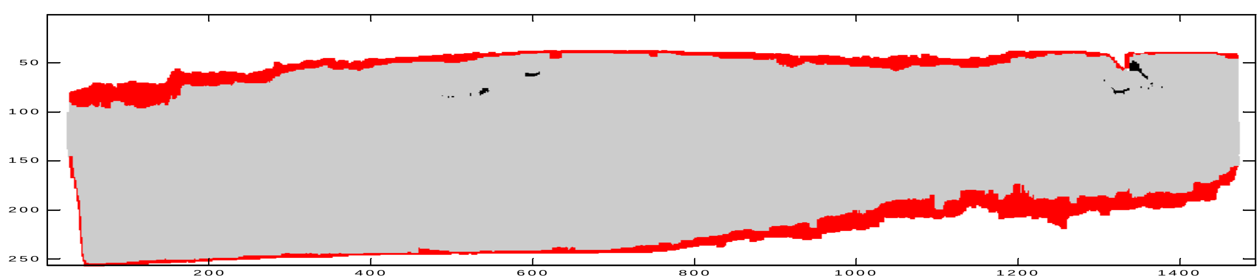


Figure 9. *Re-examination of the case in Figure 4d. The surface approximation method gives superior results over the thresholding methods that were considered.*

Acknowledgements

This work was partially supported by USDA NRI Competitive Grant #97-36200-5274.

References

Åstrand, E., 1996. *Automatic inspection of sawn wood*. Ph.D. Dissertation, Department of Electrical Engineering, Linköping University, Linköping, Sweden.

Besl, J.P., and Jain, R.C., 1988. Segmentation through variable-order surface fitting. *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. PAMI-10(2), pp.167-192.

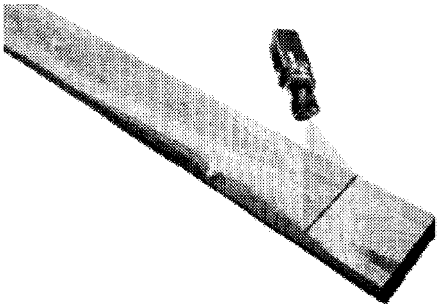
Carmo, M.P., 1976. *Differential geometry of curves and surfaces.* Prentice-Hall, Englewood Cliffs, New Jersey.

Faugeras, O., 1993. *Three-dimensional computer vision: a geometric viewpoint.* MIT Press, Cambridge, Massachusetts.

Forchheimer, R., Ingelhag, P., and Jansson, C., 1992. MAPP2200, a second generation smart optical sensor. In: *SPIE Proceedings*, vol. 1659.

Hoffman, R., and Jain, A.K., 1987. Segmentation and classification of range images. *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. PAMI-9(5), pp.608-620.

Lee, S.-M., Abbott, A.L., and Schmoldt, D.L., 1999. Using an embedded-processor camera for surface scanning of unplaned hardwood lumber. In: Thompson, D.O., and Chimenti, D.E. (Eds.), *Review of Progress in Quantitative Nondestructive Evaluation*, Volume 19. Montreal, Canada.



Proceedings:

4th International Conference on Image Processing and Scanning of Wood

IPSW 2000

21-23 August, 2000
Mountain Lake Resort
Mountain Lake, Virginia USA

D. Earl Kline and A. Lynn Abbott
Technical Editors

Sponsored by the USDA Forest Service, Southern Research Station
in cooperation with Virginia Polytechnic Institute and State University (Virginia Tech)
and the International Union of Forestry Research Organizations (IUFRO)