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# Locating and identifying splits and holes on sugi by the laser displacement sensor 

Received: June 24, 2002 / Accepted: December 4, 2002


#### Abstract

The split and the hole are two common defects on sugi (Cryptomeria japonica D.Don). They have a common feature in that they are associated with surface irregularities. We have developed a laser scanning system to detect the splits and the holes based on their thickness, which correlates spatially with the profile information. The displacements measured by the laser sensor were converted to pixel values to generate the displacement profile image. Both the splits and the holes manifested well in the image. A dedicated image-processing program written in Visual Basic has been developed. The defects regions were accurately located by the image processing. To identify the defects, eight recognition rules based on four features have been utilized. Furthermore, a method based on the pixel model was proposed to compute the area of the defect. The results indicated that the defects could be identified correctly, and the areas could be computed accurately using the pixels model.


Key words Wood defects • Laser displacement sensor • Image processing • Sugi

## Introduction

Knots, decay, splits, and holes are common defects of wood that can be detected by an experienced worker according to the Japan Agriculture Standard (JAS). To detect defects automatically, we used microwaves, ultrasound, X-rays, light reflections, and temperature gradients to detect the presence of knots. ${ }^{1-10}$ Some machine vision systems based on the color CCD camera were developed to classify all the above defects using their color properties. ${ }^{11-14}$ Holes are difficult to distinguish from the other defects with a tradi-

[^0]tional color CCD camera for wood species of sugi because the holes have color and shape features identical to those of the knots. The splits are difficult to detect because they have color and shape features identical to those of the growth ring in the captured image. What is needed to identify splits is a high-resolution image, which increases the storage data and computing time of the machine vision system. The split and the hole do have a common feature, however: They are associated with surface irregularities. One way to improve the defects-detecting efficiency is to distinguish the splits and holes from other defects.

The laser light scanning system was developed to detect the wane of the board in the machine vision system for the trimming and edging of hardwood. ${ }^{15}$ The laser light, which reflects from the surface, is different when viewed from an angle relative to the light plane. It is possible to estimate thickness values over the surface of the object using the triangulation theory. In this study we investigated the possibility of using a laser scanning system to locate and identify the splits and holes of sugi using thickness information, which correlates spatially with the profile information.

## Experiments

The materials selected for the experiment were sugi samples of $1000 \times 180 \times 20 \mathrm{~mm}$. The surfaces of these materials were finished by the planer with two knives. The feeding speed was $15 \mathrm{~m} / \mathrm{min}$ and the cutting speed was $30 \mathrm{~m} / \mathrm{s}$. The laser scanning system used to detect defects is shown in Fig. 1. The system consists of a laser displacement sensor (LSD; Keyence, LK-031), a display and control unit (Keyence, LC-D1A and C1A), a computer numerical control (CNC) working table (Funuc M180 series), and a dedicated software system developed by us. Laser light is formed on the board, and the displacement is captured when the laser light hits the board surface. The light intensity is a direct measurement of the thickness profile of the object. The board is set on a two-dimensional CNC working table so it can be transported through the laser scanning


Fig. 1. Defects detection system
system to capture the thickness profile information continuously.

A dedicated software system receives this continuous flow of displacement data and converts the sampling data into pixel values of the laser displacement profile image matrix. The dedicated program is written in Visual Basic 6.0 (enterprise edition) as a code resource. The flow chart of the program is shown in Fig. 2.

Generating the displacement profile image
The feed rate of the CNC working table was $2.4 \mathrm{~m} / \mathrm{min}$; and the response frequency of the laser scanning system was 80 Hz . The widthwise spatial resolution is $0.5 \mathrm{~mm} /$ point. The scanning line containing 340 sampling data along the widthwise direction is obtained first. Altogether, 360 scanning lines are adopted along the longitudinal direction; the step is $0.5 \mathrm{~mm} /$ line. Hence the matrix of the sampling data is $340 \times 360$ points, and the real scanning range of the board is $170 \times 180 \mathrm{~mm}$.

The direct measurement for the board from the laser displacement sensor is the displacement value. To normalize the displacements and convert them to pixel values of the displacement profile image [i.e., the 8-BPP (bit per pixel) black and white] a simple normalization is applied. The operation is denoted by the formula
$g(x, y)=d(x, y) \frac{255}{T_{\text {upper }}-T_{\text {bottom }}}$
where $T_{\text {upper }}, T_{\text {botom }}, d(x, y)$, and $g(x, y)$ are the upper and lower normalizing thresholds, the displacement value, and the desired pixel value, respectively. The upper and lower thresholds ( $T_{\text {upper }}$ and $T_{\text {bottom }}$ ) are established during a preliminary experiment. The generated displacement profile image is shown in Fig. 3b.

## Edge-preserving filtering

To enhance the contrast between the clear wood and the defects and to improve detection of defects, it is essential to


Fig. 2. Flow chart for the program. $A / D$, analog to digital
eliminate the sampling and normalizing noise and the effects of the machining roughness. An edge-preserving filtering algorithm is adopted, which is a neighbor averaging algorithm that uses the least variance as an evaluation index to avoid blurring the sharp edge of the clear wood and the defects when removing noise. ${ }^{16}$

A $3 \times 3$ subset containing the point $p(x, y)$ is adopted as a neighbor of the point $p(x, y)$, and there are nine neighbor subsets, as shown in Fig. 4. The intensity value is replaced by one of its neighbor subset's means that has a least variance. If the subset contains the edge of the clear wood and defects region, the variance of the intensity values in the area become larger. The least variance is assured that the selected subset is either the clear wood or the defects region to avoid blurring the sharp edge. The algorithm is denoted by the formulas

$$
\begin{equation*}
m_{k}=\frac{1}{9} \sum_{i=0}^{2} \sum_{j=0}^{2} g\left(x^{\prime}, y^{\prime}\right) \tag{2}
\end{equation*}
$$



Fig. 3. Generated displacement image. a Image taken by the digital camera. b Generated displacement profile image. $1,2,3,4,5$, numbers of the potential difects


Fig. 4. Nine-neighbor subsets containing the points $(x, y)$ and their center positions. Coordination of point 9 is $(x, y)$. Numbers in the circles are the center positions of the subsets
$\sigma_{k}^{2}=\frac{1}{9} \sum_{i=0}^{2} \sum_{j=0}^{2}\left[g\left(x^{\prime}, y^{\prime}\right)-m_{k}\right]^{2}$
$x_{-} g(x, y)=\left.m\right|_{\min _{0 \leqslant k s s}\left(\sigma_{k}^{2}\right)}$
where $g\left(x^{\prime}, y^{\prime}\right), m_{k}, \sigma_{\mathrm{k}}^{2}, x \_g(x, y)$, and $\left.m\right|_{\min _{0 \leq k \leq 8}\left(\sigma_{\mathrm{k}}^{2}\right)}$ are the original intensity value of the point $\left(x^{\prime}, y^{\prime}\right)$ in the $k^{\text {th }}$ neighbor subset, the mean of the $k^{\text {th }}$ neighbor subset, the variance of the $k^{\text {th }}$ neighbor subset, the intensity of the point $p(x, y)$ after filtering, and the mean of the subset that has the least variance, respectively.

The filtering procedure is described as follows: Generate the $3 \times 3$ pixels neighbor subsets containing the point $p(x, y)$; calculate the variances of the nine neighbor subsets and detect the subset where the variance of its pixel values is minimum; and change the intensity of $p(x, y)$ instead of


Fig. 5. Gray intensity histogram of the displacement profile image
the average intensity value of the selected subset. The intensity histogram after the filtering operation is shown in Fig. 5.

## Otsu threshold algorithm

The displacement values of the splits and holes are higher than those of clear wood. To separate the potential defects from the clear wood, only a single threshold is needed. The Otsu threshold algorithm is adopted, which is an automatic threshold selection method. ${ }^{17}$ The threshold algorithm is expressed by the following equations. The processed image has an intensity level range $[0,255]$ and set $k$ as any number between 0 and 255. Let $n(i), N\left(N=\sum_{i=0}^{255} n(i)\right)$ denote the frequency with which the intensity level $(i)$ occurs in the whole image and the total number of pixels in the whole image. The probability of an intensity level $[P(i)]$ is denoted by Eq. 5.
$P(i)=n(i) / N \quad(i=0,1, \ldots, 255)$
The means $\left(u_{t}\right)$ of the whole image is denoted by Eq. 6.


Fig. 6. Final threshold images. a Without the filtering operation. b With the filtering operation
$u_{t}=\sum_{i=0}^{255} i p(i)$
The whole displacement profile image is divided into two classes $\left(S_{1}\right.$ and $\left.S_{2}\right)$ at threshold $k$. We set them as $S_{1}=$ $[0,1, \ldots, k]$ and $S_{2}=[k+1, \ldots, 255]$. The probabilities [ $w_{1}^{(k)}$ and $w_{2}^{(k)}$ ] and means $\left[m_{1}^{(k)}\right.$ and $\left.m_{2}^{(k)}\right]$ of the two classes are denoted by Eqs. 7 and 8 .
$w_{l}^{(k)}=\sum_{i=0}^{k} p(i), \quad w_{2}^{(k)}=\sum_{i=k+1}^{255} p(i)$
$m_{1}^{(k)}=\sum_{i=0}^{k} i p(i), \quad m_{2}^{(k)}=\sum_{i=k+1}^{255} i p(i)$
The variances ( $\sigma_{1}$ and $\sigma_{2}$ ) of the two classes are denoted by Eq. 9 .
$\sigma_{1}^{(k)}=\sum_{i=0}^{k} p(i)\left(m_{1}^{(k)}-i\right)^{2}, \quad \sigma_{2}^{(k)}=\sum_{i=k+1}^{255} p(i)\left(m_{1}^{(k)}-i\right)^{2}$
The diversity between the $S_{1}$ and $S_{2}\left(\sigma_{\mathrm{B}}\right)$ and the diversity inside $S_{1}$ and $S_{2}\left(\sigma_{\mathrm{w}}\right)$ are denoted by Eqs. 10 and 11.

$$
\begin{align*}
\sigma_{B}^{2} & =w_{1}\left(m_{1}-m_{t}\right)^{2}+w_{2}\left(m_{2}-m_{t}\right)^{2} \\
& =w_{1} w_{2}\left(m_{1}-m_{2}\right)^{2}  \tag{10}\\
\sigma_{w}^{2} & =w_{1} \sigma_{1}^{2}+w_{2} \sigma_{2}^{2} \tag{11}
\end{align*}
$$

The variance of the whole image is denoted by Eq. 12.
$\sigma_{t}^{2}=\sum_{i=0}^{255}\left(i-m_{t}\right)^{2} p(i)=\sigma_{B}^{2}+\sigma_{w}^{2}$
To select the optimum threshold $k^{*}$ automatically, the evaluation index is denoted by Eq. 13. When the degree of separation $[\eta(k)]$ is maximum, the optimized threshold results are accomplished.
$\eta(k)=\sigma_{B}^{2} / \sigma_{t}^{2}, \quad \eta\left(k^{*}\right)=\underset{0<k<255}{\operatorname{Max}}[\eta(k)]$
where $\eta(k)$ and $\eta\left(k^{*}\right)$ are the degree of separation at $k$ and the maximum degree of separation, respectively. The segment of the laser displacement profile image at $k$ is denoted by Eq. 14.
$g^{\prime}(x, y)= \begin{cases}0 & \text { if } g(x, y) \leq k \\ 255 & \text { if } g(x, y)>k\end{cases}$
where $g(x, y)$ and $g^{\prime}(x, y)$ are the intensities of point $p(x, y)$ before segmenting and after segmenting, respectively. After the laser displacement profile image is segmented, it becomes a binary image, as shown in Fig. 6.

## Extraction of recognition features

After segmenting, the potential defects are still discrete points, and the image can be denoted as a set of \{clear wood, potential defects\}. To form the complete potential defects area, the four-adjacent connectedness component labeling operation is applied. ${ }^{18}$ All potential defect regions are found, and each such region is given a different label. The image can then be denoted as the set of \{clearwood, $R_{1}$, $\left.R_{2}, \ldots, R_{n}\right\}$ after the operation, where $R_{1} \sim R_{n}$, which has the same label, represents different potential defects regions.

The following is an example of extracting recognition features. Let $R_{j}$ be one of the potential defect regions, which has the total number point $N_{j}$ of the same label. The recognition features are extracted for each labeled potential defects region. To calculate the recognition features, the potential defects region $\left(R_{j}\right)$ is idealized as its boundary rectangle, which is determined by the two minimum values and two maximum values. The minimum and maximum values are expressed by the formulas

$$
\begin{align*}
& R_{\min X}(j)=\operatorname{Min}_{P_{l} \in R j}\left[x\left(p_{l}\right)\right] \\
& R_{\max X}(j)=\operatorname{Max}_{P_{l} \in R j}^{\operatorname{Mix}_{j}}\left[x\left(p_{l}\right)\right] \\
& R_{\min Y}(j)=\operatorname{Min}_{P_{l} \in R i}\left[y\left(p_{l}\right)\right]  \tag{15}\\
& R_{\max Y}(j)=\operatorname{Max}_{P_{l} \in R j}\left[y\left(p_{l}\right)\right]
\end{align*}
$$

where $R_{\min X}(j)$ and $R_{\min X}(j)$ are the minimum and maximum $x$ coordinate values of the potential defects region $\left(R_{j}\right)$; $R_{\min Y}(j)$ and $R_{\min Y}(j)$ are the minimum and maximum $y$ coor-

Table 1. Recognition rules for the holes and splits

| Recognition rules |  | TPOTDC |  |
| :---: | :---: | :---: | :---: |
| Feature | Thresholds | High hole | Low hole |
| Holes |  |  |  |
| Size |  |  |  |
| Width (mm) | Width $\in[5,45]$ | X |  |
| Width (mm) | Width $<5$ or width $>45$ |  | X |
| Length (mm) | Length $\in[5,45]$ | X |  |
| Length (mm) | Length $<5$ or length $>45$ |  | X |
| Shape |  |  |  |
| Roundness | Roundness $\in[0.4,2.5]$ | X |  |
| Roundness | Roundness $<0.4$ or roundness $>2.5$ |  | X |
| Compactness | Compactness $\in[1,1.23]$ | X |  |
| Compactness | Compactness $<1.23$ |  | X |
| Splits |  |  |  |
| Size |  |  |  |
| Width (mm) | Width $=5$ | X |  |
| Width (mm) | Width $>5$ |  | X |
| Length (mm) | Length $=10$ | X |  |
| Length (mm) | Length $<10$ |  | X |
| Shape |  |  |  |
| Roundness | Roundness $<0.2$ or roundness $>5$ | X |  |
| Roundness | Roundness $\in[0.2,5]$ |  | X |
| Compactness | Compactness > 1.23 | X |  |
| Compactness | Compactness $\in[1,1.23]$ |  | X |

TPOTDC, the Probability of the detect classification
dinate values of the potential defects region $\left(R_{j}\right)$; and $p_{l}$ is the lth point of the potential defects region $\left(R_{j}\right)$. The recognition features are denoted by the following formulas.
Width $=R_{\max X}(j)-R_{\min X}(j)$
Length $=R_{\max Y}(j)-R_{\min Y}(j)$
Compactness $=\frac{(\text { width }+ \text { length })^{2}}{4(\text { width } \times \text { length })}$
Roundness $=\frac{\text { width }}{\text { length }}$
The width and the length express the size of the defects region. The compactness is the ratio of the square of the sum of the width and length to the area of the rectangular boundary; and the roundness is the width/length ratio of the defects. These are the shape features that describe the various defect regions.

The defects recognition rules and thresholds are presented in Table 1. Eight recognition rules based on four features are found. A total of 280 wood samples are investigated to generate the thresholds. After the four features have been computed, rules are then applied to individual potential defects regions. All the potential defects regions are voted on according to the recognition rules for the hole and for the split. If the potential defects region is in accordance with one of the recognition rules, it gets a vote. The votes based on the defects region by all the rules are then summed, and the total votes of the holes are compared to those of the splits. The potential defects region is assigned the class (hole or split) that has the higher total votes. The identifying procedure is expressed as follows.
$C_{h}($ Ri, hole $)=0$
$C_{h}$ (Ri, split) $=0$
If $5 \leq$ width $\leq 45$ then $C_{h}(R i$, hole $)=C_{h}($ Ri, hole $)+1$
If $5 \leq$ length $\leq 45$ then $C_{h}($ Ri, hole $)=C_{h}($ Ri, hole $)+1$
If $1 \leq$ compactness $\leq 1.23$ then $C_{h}(R i$, hole $)=C_{h}(R i$, hole $)$
$+1$
$0.4 \leq$ roundness $\leq 2.5$
$C_{h}($ Ri, hole $)=C_{h}($ Ri, hole $)+1$
If width $<5$ then $C_{h}($ Ri, split $)=C_{h}(R i$, split $)+1$
If $10 \leq$ length then $C_{h}($ Ri, split $)=C_{h}($ Ri, split $)+1$
If compactness $>1.23$ then $C_{h}(R i$, split $)=C_{h}($ Ri, split $)+1$
If roundness $<0.4$ or roundness $>2.5$ then $C_{h}(R i$, split $)=$
$C_{h}($ Ri, split $)+1$
If $C_{h}$ (Ri, hole) $>C_{h}$ (Ri, split) then $R_{i}$ is hole
Else $R_{i}$ is split
The area of the defects region is calculated by the formula
Area $_{R_{j}}=\frac{\text { length } \times \text { width } \times N_{R j}}{N_{\text {total }}}$
where Area ${ }_{R_{i}}$, length, width, $N_{R j}$, and $N_{\text {total }}$ are the area of the defects region $R_{j}$, the length of the whole image, the width of the whole image, the total number of pixels in the defects region $R_{j}$, and the total number of pixels in the whole image, respectively.

## Results and discussion

The defects of the splits and holes are associated with surface irregularities. This characteristic can be used to detect

Table 2. Values of recognition features and identifying results

| NOPDR | Values of recognition features |  |  |  | Identifying value |  | Area (mm ${ }^{2}$ ) |  |  | Classification |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Width | Length | Roundness | Compactness | Hole | Split | PM | RM | VM |  |
| 1 | 16 | 20.5 | 0.78 | 1.02 | 4 | 1 | 264 | 328 | 290 | Hole |
| 2 | 4.5 | 5.5 | 0.81 | 1.01 | 3 | 1 | 25.8 | 24.8 | 28.2 | Hole |
| 3 | 16 | 9.5 | 1.68 | 1.07 | 4 | 0 | 82.6 | 152.5 | 90 | Hole |
| 4 | 17 | 14.5 | 1.17 | 1.01 | 4 | 1 | 142.5 | 246.5 | 120 | Hole |
| 5 | 5.5 | 177 | 0.03 | 8.55 | 1 | 4 | 413.8 | 973.5 | 531 | Split |

NOPDR, no. of potential defects region; PM, pixel model; RM, rectangle model; VM, visual method
splits and holes. The thickness of the splits and holes is less than that of clear wood, and their displacements measured by the laser displacement sensor are greater than those of clear wood. As shown in Fig. 4, one split and four holes contained in the displacement profile image are well shown after the displacements are converted to pixel values.

The edge-preserving filter is operated to remove the sampling, normalize noise, and eliminate the effects of the machining roughness. As shown in Fig. 5, the histogram of the displacement profile image has bimodal characteristics after the filtering operation. The dominant peak is the clear wood, and another peak indicates the potential defects. Otsu's method is sufficient to segment the image automatically, whose intensity histogram is bimodal. ${ }^{12}$ To distinguish the potential defects from the clear wood, the automatic board-based selection threshold of Otsu's algorithm is adopted. As shown in Fig. 6, the displacement profile image is correctly separated into potential defects regions and clear wood. Some white noise points are scattered in the threshold image, which form some false potential defects regions without the edge-preserving filtering operation. The contrast between the defects and clear wood is enhanced, and the threshold image is accurately separated into defects and clear wood with the filtering operation.

In this study eight rules have been determined based on four features. A total of 280 wood samples used for training data were investigated to generate thresholds for establishing recognition rules. A sample containing five defects regions was used as an example to explain the processing procedure of the system and to testify to the efficiency of the system. The values of the recognition features and the classifying results are shown in Table 2. The processed sample contains five potential defects regions (four holes and one split). The results indicate that all the defects have been identified accurately. The efficiency of the identifying rules was established by the fact that the other 47 splits and 45 holes in the wood samples, which had been selected randomly from the factory to come close to actual conditions, were detected by the system proposed here. The detection results achieved $94.5 \%$ accuracy.

The areas of the defects regions, computed based on the regular model and the pixel model developed in this study, are shown in the eighth column of Table 2. The defects regions were modeled as boundary rectangles in this study. ${ }^{13}$ The rectangular model eliminates a substantial amount of clear wood from the board considered during the evaluation process because a few defects regions are rectangles. The
split and the hole are expressed by continuous pixels that do not contain redundant pixels; hence the defects regions/ clear wood region pixel ratio can be used to measure the area of the defects region. The method based on the pixel model evaluates the area of the defects regions more accurately than the method based on the rectangular model.

## Conclusions

There is now an efficient method to identify defects separately according to their features. We have seen that the laser scanning system is inexpensive and effective for locating and identifying splits and holes. The displacement values measured by the laser displacement sensor are converted to pixel values, thereby generating a displacement profile image. The splits and holes are well seen in the image. Image processing was developed to locate and identify the defects regions. The splits and holes can be identified successfully using eight recognition rules based on four features. The areas computed by the method based on the pixel model are accurate.

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