

Defect Mapping of Lumber Surface by Image Processing for Automatic Glue Fitting

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Abstract. While automated optical inspection (AOI) is an effective means to evaluate the quality of wood product, there are very few other applications of AOI in the domestic wood factories. For example, defects of holes or cavities on the surface of wood product currently are still found and filled with glue by human labor. In this paper, we propose using the laser triangulation method of 3D machine vision, to detect defects (holes or cavities) for a large area of lumber surface, and the information collected can be used in the automatic filling machine for further filling process. This method proved to be unaffected by wood surface texture, and can identify the cavity defect with a size larger than 1 mm under the speed of 3.6 m/min for wood with 1.5 m wide.

Keywords: Automated Optical Inspection (AOI) \cdot Triangulation method \cdot Lumber surface \cdot Defect detection

1 Introduction

In the production process of the wood flooring, the staff of quality control needs to check if the surface is flat or not. If there is a hole or crack, the staff fills glue in the defect before follow-up process. Currently, the action of detection and filling glue is mostly executed manually.

In recent years, with the rise of industrial automation, regardless of the technological or traditional industries, manual production has been replaced by automated production. The products of mass production must be inspected for quality management. Manual inspection consumes a lot of human resources, and the inspectors may have different standards for the defects and feel fatigue after a period of time. These factors easily lead the defective products to go downstream. It's a situation that the manufacturers and customers are not happy to see. Nowadays, due to the fact that Automated Optical Inspection (AOI) is booming, the replacement of manual inspection with computer vision can not only improve the quality of products and maintain stability, but also can effectively reduce the waste of raw materials and human labor errors.

In 1998, DT Pham and RJ Alcock conducted a literature collation on the classification and defect detection of wood-based products based on computer vision [1]. It is suggested that Automated Visual Inspection (AVI) can detect only the wood surface, and is easy to be affected by shadows, stains, textures, and misjudgment. It also emphasized the importance of lighting in the detection system.

In 2015, Hashim et al. reviewed the automatic visual inspection of wood surfaces [2], and listed related studies using different types of sensors and combination of sensors, as shown in Tables 1 and 2. The multi-sensor approach has a better performance reported in many literatures, but the single sensor is more often used. This is because single optical sensor has the advantage of lower cost, and the ability to be quickly implemented for defect detection on wood surface [3].

Table 1. Related studies on visual sensors for inspection of wood surface defects

Vision sensors	References
Laser scanner	[4]
Optical camera	[5–7]
Optical distance	[8]

Table 2. Related studies on multi sensors for inspection of wood surface defects

Sensor fusion	References
Laser scanner	[9, 10]
Video camera	
Optical camera	[11]
Color camera	
X-ray scanner	

The area camera combined with bright-field front light illumination is used by a lot of related research [5–7, 12, 13]. Results of these research show good performance in the grading, sorting, and cutting of lumber; however, if the found defect is a sound knot on wood, we do not know if it exists a real depression on the wood surface. One approach to avoid this problem for imaging the lumber surface is based on the triangulation using a laser scanner [4], where a line laser light source with grayscale camera are the most widely used [9, 10, 14, 15]. This method has been widely used in the steelmaking industry on-line flatness measurement [16], weld quality inspection [17], and automatic tire inspection [18]. In 1999, Conners et al. patented the wood surface detection system [19] and in 2008, Taylor et al. patented the method of surface detection of wood [20]. In both patents, we can see the application of the laser triangulation method.

Most of the previous research is conducted for surface defect detection on a single and slender lumber. In this paper, we focus on a large area of wood surface for assessing the feasibility of the triangulation method.

2 Method

2.1 Laser Triangulation Method

Laser triangulation method is composed of three elements of camera, laser light source, and the target object. In the laser triangulation system, the laser light projected onto the surface of the object can be observed from the perspective of the camera. The observed stripe cannot get the true height value of the object. However, the angle between the projector and the camera combined with careful calibration can accurately deduce the height of each pixel based on the contour information on the object surface. The basic geometric model can be represented by an active triangulation system, as shown in the following Fig. 1:



Fig. 1. The basic geometry of active optical triangulation

A light projector is placed at a distance b from the camera projection center which is called baseline. The projector emits an optical plane perpendicular to the XZ plane and is at an angle θ to the baseline. If there is an object in the visible range of the camera and the light plane emitted by the projector intersects the surface of the object, then the intersection point P, and the curve formed by P projection to the image plane is called stripe. Because the points on the stripes are present in the light plane emitted by the projector, it establishes a one-to-one relationship between the image and the threedimensional coordinate system [21], and the relationship can be formulated as

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \frac{b}{f \cot \theta - x} \begin{bmatrix} x \\ y \\ f \end{bmatrix}$$

By measuring a number of objects of known heights, and recording the stripe of the image and its corresponding object height, a LUT (look-up table) can be built.

2.2 Building Look-Up Table

First, we adjust the laser projector so that projection on the platform, which is used to move the target object, can create a stripe parallel to the image plane of the x-axis. Then we place several calibration elements on the platform and record the different height of the location respectively. The following is the calibration results for the application which has the largest height of 45.15 mm. For each real height we have a corresponding position deviation from the stripe in the image, and they were recorded as (height, deviation) pairs. If there exists a linear relationship between the height and deviation, then we can use a simple interpolation method to obtain the height of each point given a deviation value.

In order to verify this linear relation, we calculate the height difference ΔH between two adjacent object points and divided by its corresponding deviation difference Δh in image, and represent it as σ (depth per pixel):

$$\sigma = \Delta H / \Delta h$$

We found that each σ is not the same, as shown in the Table 3. Therefore, if σ is used directly in the interpolation method to predict the height, there will exist a great error.

Real height (H)	Deviation in the image (h)	Depth/pixel (σ)
45.15	335	
35.15	395	0.167
25.10	451	0.179
15.07	505	0.186
5.07	557	0.192
0	583	0.203

Table 3. Depth per pixel

After observing the change of σ values, we use the curve fitting based on the least squares method to replace the commonly used linear interpolation method [22]. The relationship formula is represented as follows:

$$y = ax^2 + bx + c$$

The (h, H) pairs are used as (x, y) and substituted into the formula. Through the implementation of the Cramer's rule, we can find the parameters a, b, and c. Given these three parameters, the deviation h observed in the stripe can be used as x(h) to find the height of the surface of the object y(H). For verification, the more accurate results using quadratic curve fitting are listed in Table 4, where the errors of estimation are all less than 0.1 mm.

Real height	Forecast height	Error
45.15	45.178	0.028
35.15	35.074	0.075
25.10	25.143	0.043
15.07	15.107	0.039
5.07	5.018	0.052
0	0.019	0.019

Table 4. Using quadratic curve fitting to forecast the height of the object

Although the fitting error is small, we cannot guarantee that we can get the same deviation in the image each time for the same height of object. Because it may be affected to the surface smoothness, scratches, reflective and other factors. Therefore, we will claim the current system has an accuracy of ± 0.5 mm.

2.3 Flow of Image Processing

While controlling the rotation of the motor to move the measured object, the motor sends a pulse signal at each fixed distance (for example, from an encoder) so the position of each projected stripe can be accurately recorded. The signal triggers the camera to grab the image and each image is executed by the same image processing flow as shown in Fig. 2. We can get the object surface contour depth information for each stripe. After the entire surface of the object are scanned, the collected depth information stored in the memory can be stitched to form a 2.5D image for the scanned surface.



Fig. 2. Image processing flow

3 Results

The proposed lumber surface defect detection system is built on a desktop computer as an experimental platform. The computer has an Intel i7-6700 CPU with 16 GB memory, and Windows 7 Professional 64 bit operating system. The software development environment is Microsoft Visual Studio 2015 and using C# as the development language. The image processing library used is EmguCV.

An industrial grayscale camera of resolution 1280×1024 with a cctv lens having focal length of 16 mm was used. As for the laser, we chose a 650 nm red light laser module. Motionnet remote motion control architecture was used to control the SMMC Ezi-SERVO DC closed loop stepping servo motor for moving the target object. Motion module from the slave module sends the trigger signal to control the timing of the camera.

Figure 3(a) shows a small lumber surface acquired by a digital camera. Figure 3(b) is its corresponding 2.5D image that is generated line-by-line and then stitched together after scanning the area by the proposed method. Figure 3(c) is the result after binarizing the 2.5D to show the cavity on the lumber surface.



Fig. 3. Various image format of the lumber surface: (a) 2D image, (b) 2.5D image (3) cavity image

To acquire the 2.5D information for a wide area of wood surface, more than one camera is needed to cover the required FOV (field of view). In the following experiment, we use two identical cameras with a FOV of 197 mm and placed them side-by-side. Through the stitching in the x-direction, we can detect the lumber surface about 394 mm wide. The accuracy about 0.15 mm per pixel (197 mm/1280 ~ 0.15 mm). Figure 4(b) is the 2.5D result of the lumber surface shown in Fig. 4(a). Since the large area of the wood is made of several strips of lumber, the groove between the boards is not defect and should be removed and the final results are shown in Fig. 4(c).

In the result image, the accuracy of the x-axis is the width of the FOV divided by the resolution (that is 0.15 mm); the accuracy of the y-axis is determined by the distance between two trigger signals. At present, the defect detection is conducted by moving the lumber 1 mm for each triggered image acquisition. The grayscale value of



Fig. 4. The result image of using two identical camera

the coordinate (x, y) in the result image is the depth information. According to the rules of x and y axis above, we can find the depth and locate the defects position in Fig. 4(c).

4 Conclusion

At present, the proposed system uses two cameras to inspect the surface of the lumber board and the speed of inspection is about 95 mm per second with very stable acquisition and processing. The system can correctly find the holes or cavities on the surface of the wood, and was not at all affected by wood surface texture. In the future, we hope the system can combine with the gumming machine to automatically fill the cavities on the lumber surface. It then can reduce the cost of a large number of human resources and effectively reduce the waste of raw materials and errors caused by human labor. This eventually will lead the lumber production line gradually towards the goals of industrial automation.

References

- Pham, D.T., Alcock, R.J.: Automated grading and defect detection: a review. Forest Prod. J. 48, 34–42 (1998)
- Hashim, U.R., Hashim, S.Z., Muda, A.K.: Automated vision inspection of timber surface defect: a review. Jurnal Teknologi 77, 127–135 (2015)
- Estévez, P.A., Perez, C.A., Goles, E.: Genetic input selection to a neural classifier for defect classification of radiata pine boards. Forest Prod. J. 53, 87 (2003)
- Hu, C., Tanaka, C., Ohtani, T.: Locating and identifying splits and holes on sugi by the laser displacement sensor. J. Wood Sci. 49, 492–498 (2003)
- Estevez, P., Fernandez, M., Alcock, R., Packianather, M.: Selection of features for the classification of wood board defect. In: Ninth International Conference on Artificial Neural Networks, pp. 347–352 (1999)
- Niskanen, M., Silvén, O., Kauppinen, H.: Experiments with SOM based inspection of wood. In: International Conference on Quality Control by Artificial Vision (QCAV2001), pp. 311–316 (2001)
- Hu, C., Tanaka, C., Ohtani, T.: Locating and identifying sound knots and dead knots on sugi by the rule-based color vision system. J. Wood Sci. 50, 115–122 (2004)
- Francini, F., Longobardi, G., Sansoni, P., Euzzor, S., Ciamberlini, C.: Identification of timber deformations. J. Opt. A: Pure Appl. Opt. 4, 406–412 (2002)
- Lee, S.-M., Abbott, A.L., Schmoldt, D.L.: Surface shape analysis of rough lumber for wane detection. Comput. Electron. Agric. 41, 121–137 (2003)
- Lee, S.-M., Araman, P.A., Abbott, A.L., Winn, M.: Automated grading, upgrading, and cuttings prediction of surfaced dry hardwood lumber. In: Proceedings of 6th International Symposium on Image and Signal Processing and Analysis, pp. 371–376 (2009)
- 11. Kline, D.E., Surak, C., Araman, P.A.: Automated hardwood lumber grading utilizing a multiple sensor machine vision technology. Comput. Electron. Agric. **41**, 139–155 (2003)
- Hittawe, M.M., Muddamsetty, S.M., Sidibé, D., Mériaudeau, F.: Multiple features extraction for timber defects detection and classification using SVM. In: IEEE International Conference on Image Processing (ICIP), pp. 427–431 (2015)
- Cavalin, P., Oliveira, L., Koerich, A., Britto, A.: Wood defect detection using grayscale images and an optimized feature set. In: 32nd Annual Conference on Industrial Electronics, IECON 2006, pp. 3408–3412 (2006)
- Astrand, E., Astrom, A.: A single chip multi-function sensor system for wood inspection. In: 12th IAPR International Conference on Pattern Recognition, pp. 300–304 (1994)
- 林建忠:雷射測距技術與研究現況. Photonics Industry & Technology Development Association (PIDA) (1999)
- Molleda, J., Usamentiaga, R., García, D.F.: On-line flatness measurement in the steelmaking industry. Sensors 13, 10245–10272 (2013)
- Huang, W., Kovacevic, R.: A laser-based vision system for weld quality inspection. Sensors 11, 506–521 (2011)
- Frosio, I., Borghese, N.A., Tirelli, P., Venturino, G., Rotondo, G.: Flexible and low cost laser scanner for automatic tyre inspection. In: IEEE Instrumentation and Measurement Technology Conference (I2MTC), pp. 1–5 (2011)

- 19. Conners, R.W., Kline, D. E., Araman, P.A., Xiangyu Xiao, R., Drayer, T.H.: Defect detection system for lumber. United States Patent (1999)
- 20. Taylor, T.J., Seattle, W.: Methods for detecting compression wood in lumber. United States Patent (2008)
- 21. Trucco, E., Verri, A.: Introductory Techniques for 3-D Computer Vision, pp. 44-47. Prentice-Hall, Inc. (1998)
- 22. Alex@UEA: Least Squares Regression for Quadratic Curve Fitting. In: CodeProject (2011)