

Development of Inspection System for Wooden Chopsticks

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Abstract

Our aim is to development of the inspection system of wooden chopsticks, and in this paper, we develop the prototype for high-class disposable wooden chopsticks by computer vision technology. We propose a method of inspecting the four items of fine grain sample, coarse grain sample, unpeeled sample, and defective sample. Moreover, we addressed not only the proposal of the algorithm but development of a prototype system. We carried out the inspection experiment to 1050 samples, and evaluated quantitatively. As the results, for four items of fine grain sample, coarse grain sample, unpeeled sample, and defective sample, 98.5%, 82.2%, 98.9%, and 95.8% of F-measures were obtained.

1 Introduction

Disposable chopsticks manufacturing processes are classified into two groups by the material. One is to use the offcut, and the other is to use the whole wood. The former is a Japanese domestic manufacturing method to be used as luxury chopsticks, and the latter is a manufacturing method from import used as cheap chopsticks. Some manufacturing processes, such as the cutting process, have already been mechanized. However, superior or inferior classification based on grain and scratches are done visually by sorting worker. For this reason, the labor cost a problem of disposable chopsticks manufacturing. Our aim is to development of the inspection system of wooden chopsticks. In this paper, we develop the prototype for high-class disposable wooden chopsticks by computer vision technology.

Shirakawa et al. reported an automatic inspection system for disposable wooden chopsticks similar to our aim [1]. However, the details of the algorithms are not described, and their system has not yet been realized. We guess that their system has a problem with the actual use. As far as authors know, there is no automatic inspection system for disposable wooden chopsticks by other groups in the world. Although it is not inspection of chopsticks, Okamoto and Yonezawa developed the system which detects the direction of grain by image processing [2]. Their target is to use a filler process which is one of the finishing wood processes. Honda and Sanko proposed the automatic inspection system of dividing the defect roughly into three groups of the grain defect, the single board breakage defect, and the surface concavo-convex defect, woody flooring-material manufacturing process [3]. Although analysis of the wood texture has been studied [4], the analysis of the individual grain has not been studied.

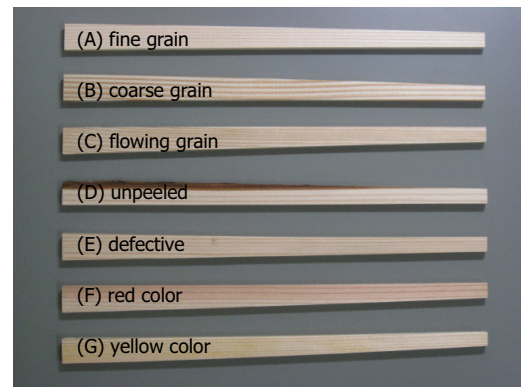


Figure 1. Sample chopsticks.

2 Overview of Inspection System

2.1 Target sample

The target sample is the disposable wooden chopsticks after cutting as shown in Fig. 1. The standard size of the target sample is 240 mm in lengths, 8mm in width of narrow side, 15mm in width of wide side, and 5mm in thickness. The material of the chopsticks is cedar. We inspect the chopsticks for high-class. The inspection items in this research are the following seven items.

- (A) Fine grain: the interval of wood grain is narrow, and wood grain is fine, namely, a sample with many wood grain.
- (B) Coarse grain: the interval of wood grain is wide, and wood grain is coarse, namely, a sample with few wood grain.
- (C) Flowing grain: the usual wood grain is flowing horizontally and straightly. However, there are grain which flows diagonal, or curving. These are classified into the flowing grain.
- (D) Unpeeled: the unpeeled sample.
- (E) Defective: there is a sample with defects, such as a spot and a worm-eaten spot. These are classified into the defective.
- (F) Reddish: reddish sample. It is an item for using Japan cedar material.
- (G) Yellowish: yellowish sample. This is the discoloration of wood resin.

All the samples are classified into either (A) or (B). The number of grain is used for the classification of (A)

and (B). Each sample is classified into zero or more items about (C)–(G). That is, there are the samples applicable to no item and two or more items.

In this paper, we focus on four items of (A), (B), (D), and (E) out of seven items. (C) is judged qualitatively visually, and the standard criteria have not been decided, and we excepted (C) from inspection items. Moreover, since it is difficult to analyze from the problem of the imaging equipment, two items of (F) and (G) are except from inspection items.

It is desirable to establish the criterion which is suitable to all the samples. However, wood is a natural object and the variation between individuals is large by the difference in a place of production or felling time. Therefore, in this paper, we take the plan which sets up a threshold so that a criterion of judgment can be adaptive.

2.2 Inspection system

The overview of the developed inspection system is shown in Fig. 2, and an example of monitor display is shown in Fig. 3. In the developed system, we used two cameras. A camera is Flea2 by Point Grey Research. For lighting, we installed two fluorescent lights of the white 20W in parallel with sample. The main PC is DOS/V PC (CPU: Intel Core2 Duo E8400 (3.00GHz) with 2GB memory).

The process flow of the system is as follows: The samples are fed into a hopper. A sample is put one on a conveyor from a hopper. This conveyor drives intermittently by a servomotor. The sample of an inspection position is taken by two cameras, and applied the proposed method. This sample is sorted based on the inspected result.

The examples IC1 and IC2 of an image taken with the two cameras C1 and C2 are shown in Fig. 4. Both the image size of IC1 and IC2 are XGA. C1 captures the narrow side and C2 captures the wide side, and the overlaps between IC1 and IC2 are about 140 pixels. The width of the narrow side of IC1 is about 63 pixels, and the width of the wide side of IC2 is about 115 pixels. Three samples conveyed on a conveyor are reflected to an image. The position of sample is located in the almost same place by control of a conveyor. This conveyor moves to above every one. Our system does not inspect three samples once, but inspect only one sample reflected within the white region in Fig. 4.

3 Region extraction

We firstly extract a sample region. The back of the right-and-left both sides of the sample is a blue back ground, and the intensity change around boundary is large. Then, we detect the vertical edge and horizontal edge, respectively, and extract a region using edge information. The extracted result of Fig. 4 is shown in Fig. 5.

4 Detection

4.1 Wood grain detection

Wood grain is used for classification of fine grain, coarse grain, and flowing grain. Grain is flowing almost

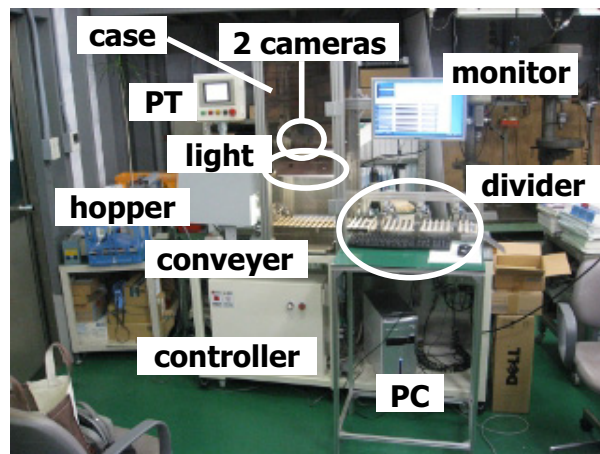


Figure 2. System overview.

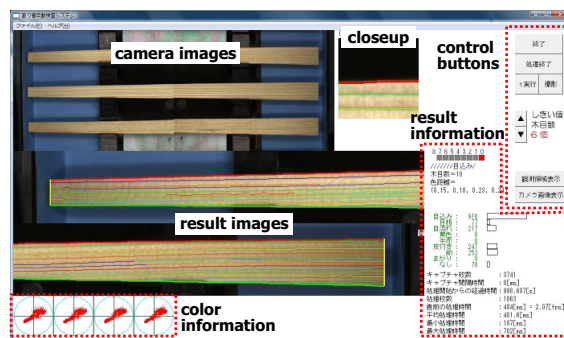


Figure 3. Main window.

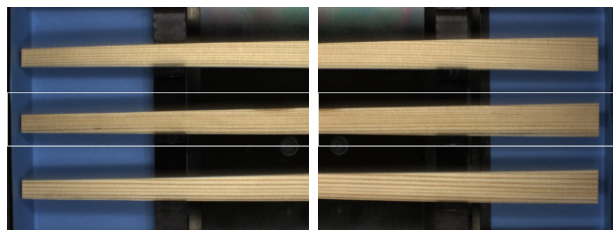


Figure 4. Sample images (left: IC1, right: IC2).

horizontally. However, since wood is a natural object, grain is not uniform and has change of the color, and change of interval of grain. Moreover, microasperity is formed in the cross section by cutting out wood. Therefore, the intensity change by microasperity is observed as a noise. In order to reduce these influences, in this paper, we do not detect grain per pixel, but detect grain per reed-shaped region which we call sub region. We divide an extraction region into the sub region which width is W_s equally as shown in Fig. 6.

To extract sample region, we used the edge value. However, ambiguous edge may be observed by the above-mentioned reason. On the other hand, observation of a perpendicular intensity change will observe the waveform according to grain, as shown in Fig. 7. Then, we apply frequency analysis to intensity change, and obtain the number of grain n_g . The spectrum waveform obtained as a result of applying a Fourier transform to the intensity transition of Fig. 7 left is

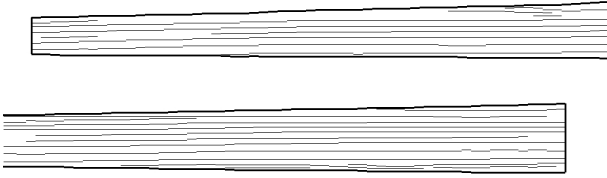


Figure 5. Extracted results (top: IC1, bottom: IC2).

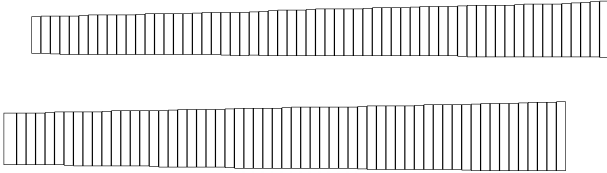


Figure 6. Sub regions (top: IC1, bottom: IC2).

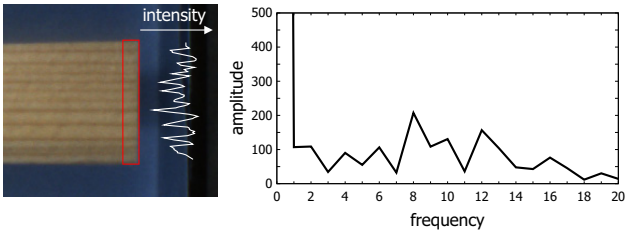


Figure 7. Grain detection.

shown in Fig. 7 right. The number of the grain of Fig. 7 is eight, and a peak is observed by the frequency 8 by a spectrum waveform.

Only by the previous processing, we can only measure the number of the grain n_g in each sub region. Moreover, only by consideration one sub region, we suppose that it is easy to be affected by noise. Thus, we measure n_g from several sub regions. In addition, we do not detect grain independently in each sub region, but we detect grain in consideration of the connectibility of a sub region next to each other. In particular, we detect n_g local maximums from the intensity waveform as grain. In this process, it is not necessary to give the threshold to the intensity, and we can detect grain without begin affected by the noise. Detected grain is connected in consideration of the spatial relationship of the grain of the neighboring sub region. Thereby, it is possible to remove the short grain as the noise. The detected result to Fig. 4 is shown in Fig. 5.

4.2 Defective point detection

There are various shape and intensity in a gnarl, a wormhole, and a dark spot. Figure 8 shows several samples of a gnarl and a wormhole. Although the wormhole can observe a clear intensity difference with the circumference, a gnarl has various intensities. Generally these points are darker than the circumference. Then, we detect the point whose intensity is lower than a surrounding region as a defective point.

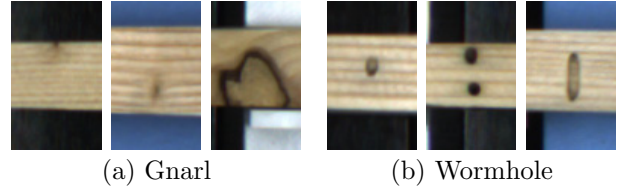


Figure 8. Defective samples.

5 Classification

5.1 Fine and coarse grain sample

The chopsticks have a wide part and a narrow part, and a wide part can observe much grain. The sorting worker of chopsticks manufacturing factory observes a wide part and classifies it into either (A) or (B). Then, we calculate the number of grain in a 200 pixel (approximately 20mm) left side region. We set a threshold T_g to divide (A) and (B). If $n_g \geq T_g$, we classify into fine grain sample, otherwise we classify into coarse grain sample.

5.2 Defective sample

When one or more defective point is detected in the target sample, we classify into the defective sample.

5.3 Unpeeled sample

The color of the bark is dark brown, and bark region is observed by the side of sample. However, since it is appeared to the side, there is a case which does not appear easily by a captured image. So, in this paper, we do not detect a bark region but analyze bark-likeness based on color information.

The circumference backgrounds of the sample are a blue part or a black part. The sample region is yellow, flesh, and red color. We observe the same range upper and lower side from the boundary of the extracted sample region. When the bark is peeled, two distributions of a background region and sample region are almost same. Conversely, when the back is unpeeled, distribution of two regions has deviation. This is because the region of unpeeled sample does not contain the bark. We classify using this characteristic.

We set a 5-pixel range of observations in the upper and lower of the extracted boundary, respectively. This observation range was decided experientially. We observe distribution of HS color space of the pixel within this observation region. As for the peeled sample, the center of gravity G_{HS} of distribution is near the center of HS color space. As for the unpeeled sample, G_{HS} is near the yellow of HS color space. Then, we give a threshold T_{HS} . If $G_{HS} > T_{HS}$, then we classify this sample into unpeeled sample.

6 Experiment

We took 1050 samples with two cameras using the developed system. We set experientially the width W_s of sub region for grain detection as 15 pixels. We set the number of threshold grain T_g to 6, and the threshold T_{HS} to 0.24. T_g is the value directed from the

Table 1. Experimental result.

inspection item	P [%]	R [%]	F [%]
(A) fine grain	97.8	99.3	98.5
(B) coarse grain	90.5	75.3	82.2
(D) unpeeled	99.8	98.1	98.9
(E) defective	93.0	98.7	95.8

chopstick manufacturing factory, and T_{HS} was the value from which the highest accuracy was obtained.

To evaluate inspection accuracy quantitatively, we calculated the correct answer visually about four inspection items. Based on the inspection result, we computed the precision P , the recall R , and F-measure F . P and R are two widely used metrics for evaluating the correctness of a pattern recognition algorithm. P is a measure of the accuracy provided that a specific class has been predicted. R is a measure of the ability of a prediction model to select instances of a certain class from a data set. F is a measure that combines P and R . These values are defined as follows:

$$P = tp / (tp + fp)$$

$$R = tp / (tp + fn)$$

$$F = 2PR / (P + R)$$

where, tp means the number of true positive, fp means the number of false positive, fn means the number of false negative.

Experimental results are shown in Table 1. As for (A) and (B), (A) is high F of 98.5% and (B) is low F of 82.2%. Though all samples are classified into either (A) or (B), many of experimental samples were classified into (A). There were only 26 coarse grain samples in our experiment. For this reason, a small number of incorrect results influenced greatly.

The inspection item (D) was obtained high accuracy of 98.9%. When a lot of bark regions are observed, it can be detected easily. However, there were samples which had difficult bark observation from the top viewpoint. The developed system is inspecting only one side of sample. It is supposed it can be easily discriminant the bark by observing the side of sample. Therefore, improvement in inspection accuracy is expected by reformation of the mechanism.

There were several defective samples having difficult discrimination visually. In the case of gnarl and wormhole as shown in Fig. 8, it is easy to classify into the defective sample. However, though the dark region was seen, such as the arrow point of Fig. 9(a), this sample was difficult to detect a dark spot. Moreover, there was also fault detection, such as the arrow point of Fig. 9(b). There were a lot of samples by which few dark points are observed.

We implemented our software by Microsoft Visual C++ and used the computer described in 2.2. The average processing time per sample was 387ms, and we confirmed that it was sufficient processing speed.

7 Conclusion

In this paper, we proposed the inspection method of four inspection items of fine grain sample, coarse grain sample, unpeeled sample, and defective sample.

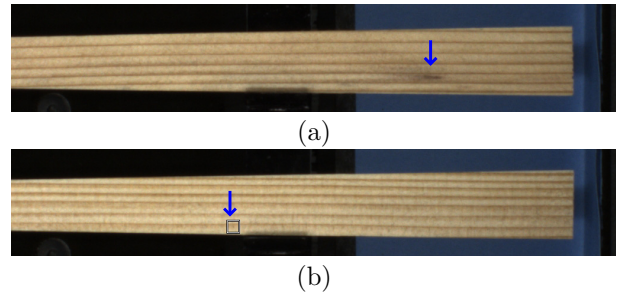


Figure 9. Inspected results.

Moreover, we addressed not only the proposal of the algorithm but development of a prototype system. We carried out the inspection experiment to 1050 samples, and evaluated quantitatively. As the results, in four items of fine grain sample, coarse grain sample, unpeeled sample, and defective sample, we obtained 98.5%, 82.2%, 98.9%, and 95.8% of F-measure, respectively. The target accuracy which the chopsticks manufacturing factory worker set up was more than 98%. Moreover, target processing speed is two samples per second. Although it is not over target accuracy by all four items, we verified the availability as a prototype system.

Although we confirmed that our method obtain a good result to four items, high precision beyond the current system is desired for utilization. Moreover, it is necessary to investigate the algorithm of remainder three items. The item of (C) flowing grain sample will be clear by establishing a criterion of decision. About (F) reddish sample, we will investigate the discriminant method using color information. It is difficult to discriminate (G) yellowish sample by the visual observation. Therefore, we will investigate including the improvement of an imaging device, such as not with visible light but with ultraviolet rays.

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References

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