Development of System to Classify Speckle Images for Visual Inspection of Cutlery

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Abstract This paper develops a system to visually inspect cutlery based on a simple machine learning algorithm using image features that are robust against overexposure. First, we develop an image acquisition apparatus comprising a laser and a screen that produces speckle images of unique shapes depending on the degree to which the photographed cutlery has been polished. The contribution of this study is to produce speckle images in this way. This enables accurate classification without newly deriving a sophisticated machine learning algorithm in the subsequent processing. We use the speckle images to develop moment-related features that represent the unique shapes and avoid the problem of overexposure. Second, we apply the extreme learning machine, a simple but representative machine learning algorithm, to the obtained features. Experimental results using real cutlery show that our developed system achieved good accuracy and precision regardless of exposure time.

Key words: polishing machine, manufacturing automation, machine vision, feature extraction, machine learning, image classification

1. Introduction

Tsubame-sanjo, located in Niigata Prefecture, Japan, is known across the world for the production of such items of cutlery as table forks and spoons [1,2]. Before the cutlery is polished, an inspector examines its edge, called the koba (in Japanese) (see Fig. 1). However, the number of skillful inspectors in the profession has decreased in Japan in recent years because of declining birthrates and an aging population*.

To tackle this problem, this paper develops a system to visually inspect the koba of cutlery. The system includes an image acquisition apparatus and a machine learning unit. As shown in Fig. 2, the koba can be classified into different states, the kiji state, kobasuri state, and kobamigaki state, according to the degree to which it has been polished**. The polishing procedure comprises the kobasuri step — rough polishing that causes the koba to transition from the kiji state to the kobasuri state — and the kobamigaki step — fine polishing of the koba from the kobasuri to the kobamigaki state. We develop a system to determine whether the polishing procedure can continue from a previous step to the next one. In other words, we automate the inspection of the koba following the kobasuri step and the final inspection after the kobamigaki step.

Several techniques have been proposed for the inspection of metal surfaces that may be applied to the visual inspection of the koba. Such methods can be divided into contact [3,4] and non-contact methods [5–7]. Contact methods damage the surface of the object by a stylus and degrade its visual quality [8]. Because visual quality is important for items of cutlery, such methods are not suitable for our purpose here. Conversely, non-contact methods do not degrade the visual appearance of the object, and involve quick measurements [9]. They include measuring roughness based on surface texture [10–12], measuring quality based on the reflected light when a pattern is projected on the surface*.

* Tsubame-sanjo industry statistics (in Japanese), http://www.city.tsubame.niigata.jp/about/008000010.html http://www.city.tsubame.niigata.jp/content/100870492.pdf
** Kiji, kobasuri, and kobamigaki are the Japanese languages used in the cutlery production scenes.
Mirror finishing process of the koba of cutlery. It comprises the kobasuri step (rough polishing) and the kobamigaki step (fine polishing). A machine learning unit in our system provides two classifiers, one to determine whether the in-process inspection is complete, and the other to determine whether the final inspection is complete.

In the experiment, we darkened the room; thus, we can ignore the ambient light and only the laser beam struck an item of cutlery.

We overcome the above limitations as follows. First, we irradiate a laser beam on the koba and project the reflected light on a screen to acquire speckle images on it. The contribution of this study is to produce these speckle images using the apparatus shown in Fig. 3. The appearances of speckle images for the kiji state, those for the kobasuri state, and those for the kobamigaki state are greatly different (examples are shown in Fig. 4). Thus, in the subsequent processing, it becomes possible to perform accurate classification without newly deriving a sophisticated machine learning algorithm.

We calculate moment-related features (image moments of the first, second, third, and fourth orders) from the acquired speckle images. Because the obtained features represent the rough shapes of the speckles, they are robust to overexposure that occurs in the
local regions of the images. Next, we adopt the extreme learning machine (ELM) [19, 20], i.e., a simple but representative machine learning algorithm. Although it is difficult to prepare training data for the koba that are comparable in amount to those used for general deep learning using Web images, the ELM can work well even with a small amount of training data. Besides the ELM, there are machine learning techniques (e.g., k-nearest neighbors (k-NN) [21] and support vector machines (SVM) [22]) that are applicable to a small amount of training data. Chy and Rahaman [23] report that the ELM achieves higher performance than k-NN and SVM. She et al. [24] show that the ELM has better generalization ability than SVM especially for a small percentage of labeled training data. For these reasons, we adopt the ELM. For the in-process inspection of the koba after the kobasuri step, we classify images of the koba into one of two states, that is, the kobasuri or the kiji states. For the final inspection after the kobamigaki step, we classify the images into one of two states, that is, the kobamigaki or the kobasuri states. Because our developed system can classify the extent to which the koba has been polished rather than measuring surface roughness values, automatic inspection without reliance on human judgment becomes feasible.

The remainder of this paper is organized as follows: Section 2 describes the cutlery used in this study and our developed system in detail. In Section 3, the results of experiments on cutlery are detailed to verify the effectiveness of our system. The conclusions of this study are given in Section 4.

2. Methodology

In this section, we explain the cutlery used for this study and our developed system, which includes an apparatus to acquire speckle images, feature extraction of the images, and classification based on the ELM.

2.1 Samples

We used table forks provided by Daiwa Mechanic Inc.* as examples of cutlery with specular reflection. For each of the kiji, kobasuri, and kobamigaki states, we prepared 30 samples. Kiji state samples were cut from a plate of a metal using a press machine. They were not well polished and contained burrs. Kobasuri state samples were formed by polishing the burrs in kiji state samples using a coarse-grained whetstone. Kobamigaki state samples were produced by polishing the surfaces of samples of the kobasuri state using a fine-grained whetstone. Their surfaces were very smooth and glossy.

2.2 Acquiring Speckle Images

A block diagram of the developed system is shown in Fig. 5. We now explain the process of acquiring the speckle images. Using an image acquisition apparatus constructed with reference to [18], we acquired speckles that represented the surface quality of the koba. Because the acquired images included speckles at a high resolution [25, 26], this was suitable for the koba (given the small size of the target of imaging). As polishing progressed, the components of specular and diffuse reflections from the koba increased and decreased, re-

*** http://www.daiwam.co.jp/
Fig. 5  Block diagram of the developed system.

Fig. 6  Angle of incidence of the laser incident. We define the angles of incidence and reflection $\theta$ using the normal of the base plane that connects edges of the koba.

Fig. 7  Examples of binary images obtained from speckle images. The speckle images used here are shown in Fig. 4 (the exposure time is 2 s).

spectively. This apparatus could capture differences in the shapes of the speckles depending on the degree to which the koba had been polished.

We now explain the scheme used to obtain the speckles using the image acquisition apparatus, which is shown in Fig. 3. We first irradiated a collimated laser beam with a wavelength, output, and spot diameter of 635 (nm), 1 (mW), and 4.5 (mm), respectively, on the koba. We defined a plane that connected the edges of koba as the base plane, as shown in Fig. 6. Following this, we irradiated the laser beam at an angle of incidence of $\theta \approx 45^\circ$ from the normal of the base plane. At this time, the cutlery was placed perpendicular to the normal of the screen. The laser beam was then diffused on the surface and the scattered light was projected on the screen, installed approximately 150 (mm) from the koba. Furthermore, we acquired the speckle images projected on the screen using a camera (body: Panasonic LUMIX DMC-DH4, lens: Panasonic LUMIX H-FS14140) installed in front of the screen at approximately 448 (mm) from it. By imaging the range, the height and width of which were 359 (mm) and 258 (mm) on the screen, respectively, we obtained RGB images, each comprising 1920 x 1440 pixels.

2.3 Binarization of Speckle Images

In this subsection, we explain the binarization of the speckle images shown in Fig. 5. In our developed system, we binarize the speckle images and calculate their moment-related features that are robust to overexposure to implement automatic visual inspection. To this end, we first extract the red components of the speckle images and generate grayscale images. Note that we extract only the red components of the RGB components to brighten the speckle images because we used a red laser beam. We then apply the Otsu’s method [27] to the grayscale images to generate the binary images. The binary images make it feasible to extract moment-related features that are robust to overexposure, as explained in the next subsection. Fig. 7 shows examples of the binary images.

2.4 Extraction of Moment-related Features

To render the careful tuning of the exposure time of the koba unnecessary, we propose a method for extracting moment-related features of the speckles that are robust to overexposure. For kiji state samples, the speckle images on the screen increased in size because the components of diffuse reflection on the rough surface were large. Conversely, for kobamigaki state samples, the speckle images on the screen decreased in size because the smooth and glossy surface enhanced components of specular reflection, and the laser beam was intensively reflected along the direction of specular reflection. Examples of speckle images are shown in Fig. 4.

We now explain the procedure for extracting moment-related features to assess the shape and size of
the speckle image on the screen. We first calculate the projection histograms [28, 29] of the binary image obtained in the previous subsection. The bins of the projection histograms correspond to positions in an image while those of ordinary histograms correspond to pixel values of an image. Thus, the projection histograms can represent both the distribution of pixel values and the shape of the foreground of an image. Specifically, the histograms $h_{\text{vertical}}$ and $h_{\text{horizontal}}$ are represented as

$$h_{\text{vertical}} = \left[ \sum_{x=1}^{W} I_{\text{binary}}(x, 1), \cdots, \sum_{x=1}^{W} I_{\text{binary}}(x, H) \right]$$

$$h_{\text{horizontal}} = \left[ \sum_{y=1}^{H} I_{\text{binary}}(1, y), \cdots, \sum_{y=1}^{H} I_{\text{binary}}(W, y) \right]$$

Here, $h_{\text{vertical}}$ and $h_{\text{horizontal}}$ are vectors that count the number of pixels with values 1 in each column and row of the binary image $I_{\text{binary}}$, respectively. $x$ and $y$ denote indices of the columns and rows of $I_{\text{binary}}$, respectively. $W (= 1440)$ and $H (= 1920)$ were the width and height of $I_{\text{binary}}$, respectively. Then, by normalizing $h_{\text{vertical}}$ and $h_{\text{horizontal}}$, we calculate vectors $p_{\text{vertical}}$ and $p_{\text{horizontal}}$ that represent the probability of appearance of speckles in each position. Furthermore, we calculate the moments of $p_{\text{vertical}}$ and $p_{\text{horizontal}}$ as follows:

$$F1 = \frac{1}{F2^2} \sum_{y=0}^{H} y \cdot p_{\text{vertical}}(y),$$

$$F2 = \sum_{y=0}^{H} (y - F1)^2 \cdot p_{\text{vertical}}(y),$$

$$F3 = \sum_{y=0}^{H} y^2 \cdot p_{\text{vertical}}(y),$$

$$F4 = \frac{1}{F2^2} \sum_{y=0}^{H} (y - F1)^3 \cdot p_{\text{vertical}}(y),$$

$$F5 = \frac{1}{F2^2} \sum_{y=0}^{H} (y - F1)^4 \cdot p_{\text{vertical}}(y),$$

$$F6 = \sum_{y=0}^{H} p_{\text{vertical}}(y)^2,$$

$$F7 = \sum_{x=0}^{W} x \cdot p_{\text{horizontal}}(x),$$

$$F8 = \sum_{x=0}^{W} (x - F7)^2 \cdot p_{\text{horizontal}}(x),$$

$$F9 = \sum_{x=0}^{W} x^2 \cdot p_{\text{horizontal}}(x),$$

$$F10 = \frac{1}{F8^2} \sum_{x=0}^{W} (x - F7)^3 \cdot p_{\text{horizontal}}(x),$$

$$F11 = \frac{1}{F8^2} \sum_{z=0}^{W} (x - F7)^4 \cdot p_{\text{horizontal}}(x),$$

$$F12 = \sum_{x=0}^{W} p_{\text{horizontal}}(x)^2.$$
vector $a_j \in \mathbb{R}^D$ and bias $b_j$. After a linear combination of the input feature vector, the output $G$ can be obtained through an activation function $g$ as

$$G(a_j, b_j, f_n) = g(a_j^T f_n + b_j).$$

If we denote the output matrix of the hidden layer by $H(F) \in \mathbb{R}^{N \times L}$, the calculation can be written as

$$H(F) = \begin{bmatrix}
G(a_1, b_1, f_1) & G(a_2, b_1, f_1) & \cdots & G(a_L, b_1, f_1) \\
\vdots & \vdots & \ddots & \vdots \\
G(a_1, b_N, f_1) & G(a_2, b_N, f_1) & \cdots & G(a_L, b_N, f_1)
\end{bmatrix}.$$

### Output layer

In the output layer, we linearly combine the outputs of the hidden layer. We denote a vector that represents labels of each training sample by $t \in \mathbb{R}^N$. $t$ is represented as

$$t = H(F)\beta,$$

where $\beta \in \mathbb{R}^k$ is the weight vector multiplied by the outputs of the hidden layer. $\beta$ can be obtained using the Moore–Penrose inverse [32] as follows:

$$\beta = H(F)^+ t.$$

In this way, we can obtain $\beta$ in the training phase. In the test phase, we use $a_j$ and $b_j$ in Eq. (1) and $\beta$ obtained from the training phase, and replace $f_n$ in Eq. (1) with the test samples. It thus becomes possible to classify each test sample by Eq. (2).

### 3. Experiments and Discussion

This section tests the robustness of our developed system to overexposure, so that the careful tuning of exposure time is rendered unnecessary, by evaluating its performance in classifying the koba. As explained in Section 1, we aimed to automate visual inspection after the kobasuri and kobamigaki steps. We constructed two classifiers, one to classify the koba into the kobasuri and kiji states and the other to classify them into the kobamigaki and kobasuri states. We compared the results obtained when using our moment-related features with those delivered when using conventional intensity-related features.

#### 3.1 Dataset

Using the image acquisition apparatus explained in Section 2.2, we acquired speckle images using a camera with an ISO speed of 400, aperture of 5.6, and exposure times of 1 s, 2 s, 4 s, 8 s, and 15 s. We obtained 30 speckle images of samples of koba in the kiji, kobasuri, and kobamigaki states. In this way, we constructed a dataset containing 450 (30 samples, five patterns of exposure time, and three states of koba) speckle images. Examples of these images are shown in Fig. 4.

#### 3.2 Compared Methods

As described in Section 1, we used the method proposed in [18] as basis. Note that it was difficult to directly compare our method with this one because the target of measurement and final output were different between them. Therefore, we mimicked the features in [18], and compared its intensity-based features with our moment-related features of speckle images. For comparison, we prepared the following two types of intensity-based features and incorporated them into the ELM, as in case of our method.

1. **Intensity histogram**

   We calculated the intensity histogram of the speckle images appearing on the screen. We first extracted the red components of the images and generated the grayscale image using these values. We then calculated the center of gravity of the grayscale image and extracted the patch with $5 \times 5$ pixels around the center of gravity. We determined the patch size so that we could mimic the size of the region, using which features were calculated in [18], on the screen. Following this, we calculated the intensity histogram of the extracted patch to obtain features with 256 dimensions.

2. **Intensity-related statistics**

   For the patch as above, we calculated statistical fea-
tures. The following features were calculated:

\[
\text{mean} = \frac{1}{255} \sum_{l=0}^{255} l \cdot p(l),
\]

\[
\text{variance} = \frac{1}{255} \sum_{l=0}^{255} (l - \text{mean})^2 \cdot p(l),
\]

\[
\text{contrast} = \frac{1}{255} \sum_{l=0}^{255} l^2 \cdot p(l),
\]

\[
\text{skewness} = \frac{1}{255} \sum_{l=0}^{255} (l - \text{mean})^3 \cdot p(l),
\]

\[
\text{kurtosis} = \frac{1}{255} \sum_{l=0}^{255} (l - \text{mean})^4 \cdot p(l),
\]

\[
\text{energy} = \frac{1}{255} \sum_{l=0}^{255} p(l)^2,
\]

where \( l \) is the intensity ranging from 0 to 255, and \( p \) is the intensity histogram. In this way, we prepared features based on intensity-related statistics with a six dimensions.

3.3 Results and Discussion

We use accuracy and precision as evaluation metrics as follows:

\[
\text{accuracy} = \frac{TP + TN}{TP + FP + TN + FN},
\]

\[
\text{precision} = \frac{TP}{TP + FP},
\]

where \( TP, TN, FP, \) and \( FN \) are the numbers of true positives, true negatives, false positives, and false negatives, respectively. \( TP \) and \( TN \) represent samples correctly classified as positive and negative samples, respectively, and \( FP \) and \( FN \) represent those that were incorrectly classified as positive and negative samples, respectively. The higher the accuracy was, the more accurate were the results of the classification. Because our experimental data were balanced, the resulting accuracy was suitable for the evaluation. Also, precision represents how accurately the target could be classified.

To maintain the strength of a given brand of cutlery, it should not be incorrectly classified belonging to a low-quality class. Because precision is suitable for evaluating the number of such incorrect classifications, we used this metric.

By performing five-fold cross validation [33], we evaluated classification performance when incorporating our moment-related features as well as the above two types of features into the ELM. By the grid search [34], we determined the number of neurons \( L \) and the activation function \( g \) from \( L \in \{1, 2, 3, \cdots, 20, 30, 40, \cdots, 100, 150, 200, \cdots, 1000\} \) and \( g \in \{ \text{the hyperbolic tangent function, the triangular basis transfer function, the hard-limit transfer function, the sine function, the inverse triangular basis transfer function, the sigmoid function, the soft-limit transfer function, the Gaussian function, the multiquadric radial basis function, the inverse multiquadric radial basis function} \} \). In the subsequent sections, we show two kinds of experiments, i.e., verification of performance limitation in the developed system and verification of the performance in the realistic situation.

(1) Verification of Performance Limitation

Here, we verify the performance limitation in the developed system. We evaluated the results of the in-process inspection and the final inspection of the samples. As described in Section 1, we determined whether the production of the cutlery could proceed from the previous to the next step. Therefore, for the in-process inspection (classification of samples as belonging to the kobasuri or the kiji states), we defined the positive samples in Eqs. (3) and (4) (the target of identification) as images of samples belonging to the kobasuri state.

We trained 10 classifiers (two kinds of classifiers for the in-process inspection and the final inspection, and five patterns of exposure time). For example, we describe how to train the in-process inspection classifier in which the exposure time was 2 s. First, we prepared 60 images when the exposure time was 2 s, which included 30 images of the kiji state and 30 images of the kobasuri state. Second, according to the five-fold cross validation, we divided 60 images into 48 training images and 12 test images. Third, we calculated the accuracy when we applied the classifier with multiple parameters described in Section 3.3 to the test images. Finally, we selected parameters that yielded the highest accuracy and performed evaluation. For other classifiers, we determined parameters to perform evaluation in the same manner.

The accuracy and precision of classifying samples as belonging to the kobasuri state in the in-process inspection are shown in Fig. 9. Similarly, for the final inspection (classification of samples as belonging to the kobamigaki or the kobasuri states), we defined the positive samples as images of kobamigaki state samples. The accuracy and precision of classifying samples as belonging to the kobamigaki state in the final inspection are shown in Fig. 10. Figs. 9 and 10 show that the performance of the other methods deteriorated with exposure time, that is, the degree of overexposure in the speckle
(a) Fig. 9 Comparison of the performance limitation in terms of classifying the koba-suri and kiji states. The red plots denote the performance of the method described in Section 3.2 (1): “Intensity histogram.” The purple plots show the performance of the method described in Section 3.2 (2) “Intensity statistics.” The performance of our developed system using our moment-related features is represented by the blue plots. (a) Comparison of accuracy. (b) Comparison of precision of classifying samples as belonging to the kobasuri state.

(b)

(2) Verification of Performance in Realistic Situation

Here, we verify the performance of our developed system in the realistic situation. Different from the previous section, we determined parameters of classifiers using only training images. First, for each classifier, we prepared 48 training images and 12 test images in the same manner as the previous section. Second, for each classifier, we performed four-fold cross validation for the 48 training images and calculated the mean of the accuracy. Third, we selected parameters that yielded the highest mean; then, we trained each classifier with the selected parameters using the 48 training images. Fi-
Finally, we performed evaluation with the 12 test images using the trained classifiers. Figs. 11 and 12 show the accuracy and precision for the in-process inspection and the final inspection. We can see that our developed system maintained good performance regardless of exposure time unlike the other methods. Therefore, we confirmed the effectiveness of our developed system in the realistic situation as well.

### (3) Limitation of Our Developed System

Fig. 13 shows correct and incorrect examples by the classifier of the kobasuri and kobamigaki states. Note that the classifier was constructed in Section 3.3 (2). The exposure time for obtaining speckle images in these figures was 2 s. Figs. 13(a) and (b) show that our moment-related features can capture unique shapes of speckle images for the kobasuri and kobamigaki states. Conversely, Fig. 13(c) shows the result that was erroneously classified to the kobamigaki state although the actual class is the kobasuri state. Fig. 13(c) does not reveal the unique shape of the kobasuri state, i.e., the diffusion of pixel values to the horizontal axis. This may result in the incorrect classification.

Finally, we consider the limitation of our developed system. The above incorrect result occurred when the exposure time was 2 s. When the exposure time is too short, underexposures are likely to occur in the speckle image. This may cause the difficulty of capturing unique shapes of the speckle images for each class. In such a case, our developed system using moment-related features cannot work well. In the future, we should
quantitatively investigate the relationship between the exposure time and the classification performance.

4. Conclusion and Future Work

A system to automate the visual inspection of koba, that is, the edge of an item of cutlery, is important. The performance of currently available methods for its visual inspection may suffer from overexposure due to specular reflection from the cutlery. To solve this problem, we developed an image acquisition apparatus comprising a laser and a screen that generates laser speckle images with unique shapes depending on the degree to which the koba has been polished. The produced speckle images enabled accurate classification without newly deriving a sophisticated machine learning algorithm in the subsequent processing. Specifically, we developed moment-related features that can represent these unique shapes while avoiding the problem of overexposure. Finally, by applying the ELM, a simple but representative machine learning algorithm, to the obtained features, it became possible to determine whether the koba had been adequately polished. Experiments were conducted on the in-process inspection (classification of samples as belonging to the kobasuri or the kiji states) and the final inspection (classification of samples as belonging to the kobamigaki or the kobasuri states) of samples of cutlery. The results show that our developed system is more robust to overexposure than other methods. We also confirmed that our system does not incorrectly classify low-quality samples as belonging to the class of high-quality items of cutlery.

Because the quality of the koba is especially important for cutlery, we focused on it as the target of visual inspection in this paper. However, our system can be applied to other parts of cutlery or other products with specular reflection, such as surgical knives. We are interested in developing such applications in the future.

Future work should also focus on an industrial robot to implement a fully automated polishing system. It will be necessary for the robot to have functions such as automatic shape measurement [35] and automatic polishing.

We notice that the ELM used in this study has a merit of high extendability. In the future, if training data increases through our system operations, variants of ELM [36–38] will be useful for the performance improvement.

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