Defect Detection for Improving Inspection Process

Using Orthogonal Array: A Case Study of Cylindrical Metal Products

Tatsuya IWASAWA¹, Kenta YOSHIDA², Natsuki SANO³,
Mirai TANAKA⁴, Tomomichi SUZUKI⁵

1.2.5 Tokyo University of Science, 2641 Yamazaki, Noda-shi, Chiba-ken, Japan

3. Onomichi City University, 1600-2 Hisayamada, Onomichi, Hiroshima, Japan

4. The Institute of Statistical Mathematics 10-3 Midori-cho, Tachikawa, Tokyo, Japan

**contact author's e-mail address: 7416607@ed.tus.ac.jp*

Abstract:

Currently, mass production of products has become possible owing to the advances in manufacturing technology, enabling the manufacture of products in larger quantities and at higher rates than that done previously. The inspection processes for detecting nonconforming products must be performed at higher speeds without any loss in accuracy. This has motivated the use of online inspection machines such as cameras that detect defective products in many inspection processes. However, accurate criteria must be set for such online inspection machines to distinguish between the non-defective and defective products. In this study, we focus on inspection techniques used to improve the classification accuracy of an actual inspection process. While previous studies have improved the classification accuracy by using a significant amount of preprocessing and feature-extraction calculations, neither to what extent each method affects the accuracy nor how to combine the different methods to improve the accuracy is known. We introduce orthogonal arrays to test the effect of several factors by performing a few experiments. In this study, we construct an optimal combination of methods using the orthogonal array to achieve a higher accuracy and demonstrate that the resulting combination of methods does, achieve a higher classification accuracy than the previous methods.

Keywords

Preprocessing, Classification accuracy, Feature extraction, Image processing, Optimum level

1. INTRODUCTION

Mass production of products has become possible due to the advances in the manufacturing technology that enables the manufacture of products in larger quantities and at higher rates than that done previously. However, these developments have introduced quality assurance issues such as food sanitation because inspection processes must also be conducted at higher rates. To maintain the necessary high quality, online inspection machines such as cameras that detect defective products have been used in several inspection processes. However, the use of such online inspection machines requires the use of accurate criteria for distinguishing between the non-defective and defective products. Improper inspection criteria allow defective products to be shipped, degrading product quality. To overcome this drawback of online inspection machines, proper inspection criteria must be determined. Many approaches have been investigated for accurately distinguishing between the non-defective and defective products.

For example, Md. et al. (2016) proposed a method for the detection of various defects in textile fabrics using statistical techniques, while Giacomo et al. (2015) presented a new approach that classifies color and texture fruit surface defects using a machine learning method and Selvi M. et al. (2014) proposed a method for the detection of steel surface defects using image processing techniques.

The present study focuses on the identification of defects by analyzing the images of the internal surface of cylindrical metal products obtained by a camera positioned directly above the product. Our inspection approach uses three steps to distinguish between good and defective products. First, the preprocessing step emphasizes the defects. Then, the feature-extraction step defines several variables to distinguish between the good and defective products. Finally, the classification step distinguishes between the good and defective products. This approach builds on the contribution of Karasawa (2015), who improved the classification accuracy by using the MT method, which is one of the distinction methods used in the classification step. However, even after using such sophisticated methods, it is difficult to improve the accuracy without the appropriate preprocessing and feature extraction. To address this issue, Sano et al. (2016) and Itou (2014) improved the classification accuracy by using various methods in the preprocessing and feature-extraction steps. However, it is still unclear how each method influences the classification accuracy and how these methods should be optimally combined to improve classification accuracy. Thus, the purpose of this study is to develop new methods to improve the sorting accuracy and to optimally combine these methods to achieve a greater sorting accuracy. It is found that the optimal combination of methods did achieve a higher classification accuracy than the previous methods.

The outline of this paper is as follows. The image data are summarized in Section 2 and the many methods used in the preprocessing and feature-extraction steps and the orthogonal table for combining these methods to achieve a higher sorting accuracy are described in Section 3. In Section 4, we present our experimental results. In Section 5, we compare the accuracy of the method used in a previous study to the results obtained using the proposed method. Finally, Section 6 summarizes this paper and provides some recommendations for future research.

2. PRODUCTS

2.1 DATA

In this study, a cylindrical metal product is used as an example. To sort the products, we first image the inside of the cylindrical metal products using the camera positioned directly above the product and then convert the image into polar data. We use this procedure because it is difficult to directly obtain the data due to the cylindrical shape of the products.

Next, we convert the polar data into RGB values, which are the numerical values designating a particular color. For example, various levels of red, green, and blue are each assigned a number between 0 and 255, and the overall color is designated by a triplet of these eight-bit numbers. To facilitate defect detection, we use the HSL (hue, saturation, and lightness) range that unifies the three colors into a single RGB value.

Following Sano et al. (2016), who found that defects are difficult to detect in some product areas because of the light and shape of the product, we also analyze the lower part of the cylindrical metal products. We, therefore, divide the lower part of the products into three areas to facilitate the analysis.

Although dirt and dents are not allowed on good products produced at the factory, these products may exhibit small patterns that appear similar to dents or dirt. To develop more stringent criteria, we analyze the pseudo-defective sample products attached to the seals.

2.2 DEFECT FEATURES

Sano et al. (2016) detected the defects by analyzing the waveform data instead of using a direct analysis of the rows and columns (i, j) of the matrix data. To detect the defects, we also examine the characteristic waveforms. Figure 1 shows the waveform for an average product height (i.e., the average of a row of the matrix data).

Figure1. Waveform data from sample product. A defect is included in the waveform data near row 470. With the exception near row 470, waveform data do not include any defects

Figure 1 shows a relatively large sample of a given defect containing high and low points. Near row 470, the waveform suddenly dips because of the defects. The defects can be identified by the sudden changes in the numerical values rather than by the mean maximum or minimum. Therefore, the detection of small defects is difficult because such defects cause small changes in these numerical values.

3. ANALYSIS

3.1 OVERVIEW OF ANALYSIS

Several preprocessing and feature-extraction methods have been introduced by Itou (2014) and Sano et al. (2016). As mentioned in Section 2, detection of small defects is difficult and some type of preprocessing after the polar conversion is required to facilitate their detection. However, neither to what extent each method affects the detection accuracy nor how different methods can be combined to improve the accuracy is known. We, therefore, introduce orthogonal arrays to test the effects of many factors by performing several experiments. The main effects and interactions considered in this study are shown in Table 1. We use an L_{32} orthogonal array and perform 32 experiments for each area of the product and then calculate three accuracies from each experiment with the overall accuracy of each experiment defined as the average of the three accuracies. We then convert these results by using the logit function and use them as the characteristic values. After analyzing the variance, we determine the optimum level and the optimum combination of the methods for each product area.

Previous studies have shown that “feature quantity extraction with window” (FQEW) and “one difference” (OD) are especially effective for improving the accuracy; therefore, we insert four-level FQEWs and ODs into the orthogonal array. The first-level factor is “Used,” and the second-level factor is “Not used.” If the first level is selected, then we use this method to calculate the accuracy. If the second level is selected, we do not use this method to calculate the accuracy. We present the orthogonal table in the Appendix (Table 5).

In this study, we calculate the accuracy by using support vector machine (SVM). To analyze how to combine the preprocessing and feature-extraction methods, we use a distinction method that dispenses with variable selection and, therefore, introduce the SVM. The preprocessing methods, feature-extraction methods, and SVM are explained below.

Table1. Assignment of factor names and levels. We assign two-level to symbol A–F and four-level to symbol E–G. We also consider eight pattern interactions.

Symbol	Methods and Features	Level			
		1	2	3	4
A	Overlap	Use	Not use		
B	Nonlinear density conversion	Use	Not use		
C	Gaussian filter	Use	Not use		
D	Laplacian filter	Use	Not use		
H	Maximum value	Use	Not use		
I	Minimum value	Use	Not use		
J	Variance	Use	Not use		
K	Kurtosis	Use	Not use		
L	Skewness	Use	Not use		
M	Range	Use	Not use		
N	EHOG feature quantity	Use	Not use		
O	Texture characteristic quantity	Use	Not use		
F	Operation of the row	Variance	Maximum		
E	Feature quantity extraction with window (size of window)	10×1	20×1	10×4	20×4
G	One difference (number of lags)	Not use	1	3	5
E×F	Feature quantity extraction with window×Operation of the row				
E×F					
E×F					
E×D	Feature quantity extraction with window×Laplacian filter				
E×D					
E×D					
B×O	Nonlinear density conversion× Texture characteristic quantity				
B×C	Nonlinear density conversion× Gaussian filter				
F×K	Operation of the row×Kurtosis				
F×J	Operation of the row×Variance				
F×M	Operation of the row×Range				
F×H	Operation of the row×maximum value				

3.2 PREPROCESSING METHODS

3.2.1 NONLINEAR DENSITY CONVERSION

We consider the overlap for three product areas. Each overlap adds three columns of data to an area from the columns of the adjacent areas. For example, three columns of data from Areas 1 and 3 are added to Area 2 as shown in Figure 2. We call this the “overlap” operation.

Figure 2. Example of overlap operation for Area 2. Three columns from Area 1 and three from Area 3 are added to the data for Area 2, resulting in $x + 6$ columns of data for Area 2.

3.2.2 NONLINEAR DENSITY CONVERSION

We use dark green light to image products so that the images appear dark green. The difference between the bright and dark zones of the image is small, making it difficult to differentiate between the defective and normal products. To produce more clear and lighter images, we introduce the “nonlinear density conversion.” Nonlinear density conversion is effective for the images where the density values concentrate around a certain value. Therefore, this method improves the image contrast enabling clear distinction between the bright and dark zones. For a detailed explanation, see Sakai (2010). The nonlinear density conversion is given by

$$f'(x, y) = \begin{cases} 2f(x, y) \left(\frac{f(x, y)}{z} \right)^2 & \left(f(x, y) \leq \frac{z}{2} \right) \\ \frac{z}{2} \left(1 + \sqrt{\frac{2f(x, y) - z}{z}} \right) & \left(f(x, y) > \frac{z}{2} \right), \end{cases} \quad (1)$$

where $f(x, y)$ represents a numerical value in the HSL range and z is the maximum HSL value and is equal to 255.

3.2.3 GAUSSIAN FILTER AND LAPLACIAN FILTER

As can be seen from Figure 1, noise removal and edge detection must be performed for the images, necessitating the introduction of the noise removal and edge detection methods. In the edge detection studies, such as those by Marr et al. (1980) and Huertas et al. (1986), the “Gaussian filter” and “Laplacian filter” are often used for noise removal and edge detection, respectively, due to the effectiveness of these methods.

Generally, the luminosity C (the brilliance) near a given pixel differs only slightly from that at the given pixel, whereas the luminosity C far from a given pixel often differs from that at the given pixel. A Gaussian filter increases (decreases) the pixel weight for the pixels close to (far from) the given pixel. The Gaussian filter is given by

$$f(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right), \quad (2)$$

where $\sigma = 0.849$ is generally used (Takagi et al. 2011). Applying the Gaussian filter (2) to the image data smoothes the image and smears out the low-level noise.

Generally, the Laplacian filter is applied to the images that have been smoothed by the Gaussian filter, because this method is sensitive to noise. The Laplacian filter is given by

$$\nabla^2 f = f(i-1, j) + f(i+1, j) + f(i, j-1) + f(i, j+1) - 4f(i, j). \quad (3)$$

Here, i (j) is the row (column) value. Next, we apply “sharpness processing,” which subtracts the Laplacian from row i and column j of the matrix data (i.e., $f - \nabla^2 f$). This method emphasizes the edges and defects.

3.2.4 FEATURE QUANTITY EXTRACTION WITH WINDOW

Sano et al. (2016) proposed the FQEW method, which creates a rectangular ($m \times n$) window and calculates the range by subtracting the minimum value from the maximum value in the window. To obtain the range for the entire matrix of the data, the window is moved from the upper-left corner of the data matrix to the lower-right corner, and the range of the data is the maximum range found for all window positions.

The FQEW method involves the following steps:

Step 1: Start with an $m \times n$ window positioned in the upper-left corner of the matrix [i.e., $(i, j) = (0, 0)$].

Step 2: Calculate the range for the window in its present position.

Step 3: Move the window one column to the right (i.e., $j \rightarrow j + 1$) until it reaches the right edge of the matrix.

Step 4: Shift the window down one row and back to the left edge of the matrix.

Step 5: Go back to step 2 and repeat until the window reaches the bottom-right corner of the matrix.

Because we use four levels in the orthogonal array experiments, we use window sizes of 10×1 , 20×1 , 10×4 , and 20×1 .

Figure 3. Feature quantity extraction with window. The window is moved from the upper-left to the lower-right corner of the matrix. Values of each positions calculated by subtracting the minimum value from the maximum value in each window.

3.2.5 ROW OPERATIONS

After applying the FQEW method, we change row i and column j of the matrix data into the waveform data. The statistics data are obtained from row values, corresponding to the height of the given product. In Table 1, we use either the maximum value or the variance from a row to create the waveform data.

3.2.6 DIFFERENCE

We take the difference between the continuous waveform data to emphasize the edge in the waveform data:

$$z_n = x_n - x_{n-k}. \quad (4)$$

Here, x_i is the characteristic value of row i and Z_n is the difference between the characteristic values of two rows separated by k . We set $k = 1, 3, 5$ when we use an orthogonal table.

3.3 FEATURE-EXTRACTION METHODS

3.3.1 DESCRIPTIVE STATISTICS

After taking the difference, we use the feature quantity, which is effective for the detection of the defects. To do this, we introduce six statistical properties: maximum value (*max*), minimum value (*min*), variance (σ^2), skewness ($\sqrt{b_1}$), kurtosis (b_2), and range ($max - min$).

3.3.2 TEXTURE CHARACTERISTIC QUANTITY

Baraldi et al. (1995) investigated the meaning of six texture features: energy, contrast, variance, correlation, entropy and inverse difference moment; these features are considered to be the most relevant among the 14 features originally proposed by Robert et al. (1973). Sano et al. (2016) also showed the effectiveness of the use of entropy, energy, and contrast for cylindrical metal products. Therefore, we introduce these three texture features to increase the statistical power of defect detection.

The density-level frequency $H(l)$ ($l = 0, 1, 2, \dots, 15$) is determined by row i and column j of the matrix data and is normalized by dividing it by the sum of all density-level frequencies. This normalized density-level frequency is denoted by $P(l)$. The entropy f_1 , energy f_2 , and contrast f_3 are given by

$$f_1 = -\sum_{l=0}^{15} P(l) \log P(l), \quad f_2 = -\sum_{l=0}^{15} P(l) \log P(l), \quad \text{and} \quad f_3 = \sum_{l=0}^{15} l^2 P(l). \quad (5)$$

3.3.3 FEATURE QUANTITY: EXTENDED HISTOGRAM OF ORIENTED GRADIENTS

Histograms of oriented gradients (HOG) proposed by Dalal et al. (2005) are very effective for image recognition, because this method can easily find the edge in the images. However, the calculation of the HOG feature is quite time-consuming because of its complicated algorithm. To reduce the calculation time, the method of extended histograms of oriented gradients (EHOG) was introduced in the work of Daimeng et al. (2013). In the present study, our approach requires the calculation time to be suitably low to enable the use of the proposed method in the mass production of the products. Therefore, we introduce EHOG to detect the defects that are the edges in the images.

The feature quantity determined by the EHOG focuses on the change in the gradient over a local area and thereby detects the edge in the images. In other words, the EHOG feature gives the edge direction in a cell. The edge direction D given by EHOG is

$$F_b(D) = \sum_{i \in D} \frac{g_b(i)}{Z_b}, \quad (6)$$

where

$$Z_b = \sum_{i=0}^n g_b(i) \quad (7)$$

is the strength of all edge directions and g_b is the strength of all edges in a direction b .

3.4 CLASSIFICATION

The SVM is a learning method and is introduced here because we must separate the data into two classes (Bernhard et al. 1992). First, we enter the learning data for which the SVM class is known. Next, we enter the test data for which the SVM class is unknown. The SVM determines the class of the test data. The learning data are given by $x_1, x_2, \dots, x_n$, which is a feature vector. The class $y_i \in \{-1, 1\}$ corresponds to each feature vector. If the class is nonlinearly separable, it is given by

$$\text{maximize } \sum_{n=1}^N a_n - \frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N a_n a_m y_n y_m k(x_n, x_m) \text{ s.t. } 0 \leq a_n \leq C, \quad \sum_{n=1}^N a_n y_n = 0. \quad (8)$$

where $k(x_n, x_m)$ is called the “kernel function;” in this study, we use the Gaussian kernel. The SVM finds the a that maximizes Eq. (8). The parameter C controls the strength of the constraint condition and the separate hyperplane is given by

$$f(x) = \sum_{n=1}^N a_n y_n k(x_n, x_m) + b. \quad (9)$$

The SVM requires that we specify the hyperparameters C and σ^2 , which is done using a grid search because the SVM suffers from the phenomenon of “over-fitting” where the hyperparameters reproduce the training data well but are not accurate for the test data. In this study, we predict the accuracy using three-fold cross-validation.

4 RESULTS

The optimum combinations of the methods are given in Table 2 for product Areas 1, 2, and 3.

Table 2. Optimal combinations of methods for each product area. Left, center, and right tables are for Areas 1, 2, and 3, respectively. Nine symbols (B, C, E, F, G, H, K, M, and O) are selected for Area 1, and seven symbols are selected for Areas 2 and 3.

Symbol	Method name (Area1)	Symbol	Method name (Area2)	Symbol	Method name (Area3)
B	Nonlinear density conversion	E	Feature quantity extraction with window (10×1)	D	Laplacian filter
C	Gaussian filter	F	Operation of the row (Variance)	E	Feature quantity extraction with window (20×1)
E	Feature quantity extraction with window (10×1)	G	One difference (lag 5)	F	Operation of the row (Variance)
F	Operation of the row (maximum value)	H	Maximum value	G	One difference (lag 3)
G	One difference (lag 1)	K	Kurtosis	I	Minimum value
H	Maximum value	M	Range	K	Kurtosis
K	Kurtosis	N	EHOG feature quantity	M	Range
M	Range				
O	Texture characteristic quantity				

Table 3 shows the result of the point estimate and 95% section estimate for each optimum combination of methods. The results of the point prediction and 95% prediction interval in each area are shown in Table 4.

Table 3. Results of the point estimation and 95% section estimate in Areas 1, 2, and 3.

	95% lower-confidence bound	Point estimation	95% upper-confidence bound
Area1	83.2%	85.7%	87.9%
Area2	81.4%	85.6%	89.0%
Area3	88.5%	90.8%	92.7%

Table 4. Results of point prediction and 95% section estimate in Areas 1, 2, and 3.

	95% lower-confidence bound	Point prediction	95% upper-confidence bound
Area1	81.4%	85.7%	89.2%
Area2	78.7%	85.6%	90.5%
Area3	87.1%	90.8%	93.6%

Area 1 gives a noisy and dark image because it is near the bottom of the product and is far from the camera. To reduce the noise and create a brighter image, we apply the Gaussian filter and the nonlinear density conversion. The data matrices of Areas 1 and 2 are smaller than that of Area 3. Defects in Areas 1 and 2 can be detected from the waveform data created using small windows in the FQEW method. Conversely, the data matrix for Area 3 contains over twice as many columns as the matrices of Areas 1 and 2. Thus, the defects are not sufficiently detectable when the waveform data are created using a 10×1 window in the FQEW method. However, if the window size is too large, the noise in Area 1 increases. Thus, a 20×1 window is optimal for Area 3.

The Laplacian filter is used in the optimum combination of methods for Area 3 because the defects are not sufficiently detectable within the waveform data when using only the FQEW method.

5 DISCUSSION

Using the HSL range, we compare the results obtained in the present study for the optimal combinations of methods with those of the method used by Sano et al. (2016) that showed the highest accuracy among all previous studies. As in the work of Sano et al., we use 72 good samples and 216 defective samples. As shown in Figure 4, in all areas, our approach leads to 7% higher accuracy compared to that obtained by the method of Sano et al.

Figure 4. Comparison of detection accuracy obtained using the method of Sano et al. and the proposed optimal combination of methods. Accuracy of the method of Sano et al. is shown by white bars and that of the proposed optimal combination of methods by black bars. The accuracy of the proposed optimal combination of methods is higher than that for the method of Sano et al. for the three Areas.

This result shows the power of finding the optimum combination of methods for each area. By contrast, Sano et al. (2016) used a single method for the detection of the defects in all areas. Higher accuracy is obtained with the proposed approach because the optimum combination of methods applies the methods that are optimally suited for the detection of the defects in each area. This study also introduces nonlinear density conversion, which provides clearer and lighter images, and the EHOg feature quantity, which improves the edge detection in the images. The application of these methods for appropriate areas improves the defect detection accuracy.

6 CONCLUSION

This study proposes a method to improve the accuracy and customizability of automated image-based defect detection. The method involves orthogonal array experiments using 15 preprocessing methods and features. The accuracy is improved because the approach uses the optimal combination of methods and features for each product

area; this is necessary because the image characteristics differ between the different product areas.

This study focuses on analyzing the preprocessing and feature-extraction steps. For a further improvement in the accuracy, we will analyze the classification step in a future study. Furthermore, by exploiting several recently developed machine learning methods such as AdaBoost and Random Forests, we can analyze the combination of preprocessing, feature extraction, and classification to improve the overall defect detection accuracy.

REFERENCES:

- [1] Baraldi A. and Parmiggiani F. (1995), "An investigation of the textural characteristics associated with gray level cooccurrence matrix statistical parameters," *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 33, No. 2, pp. 293-304.
- [2] Bernhard E. Boser, Isabelle M. Guyon and Vladimir N. Vapnik (1992), "A training algorithm for optimal margin classifiers," *In Proceedings of the fifth annual workshop on Computational learning theory*, pp. 144-152.
- [3] Daimeng W., Yong Z., Ruzhong C. and Guoliang L. (2013) "An enhanced Histogram of Oriented Gradient for pedestrian detection," *2013 Fourth International Conference on Intelligent Control and Information Processing*, pp. 459-463.
- [4] Dalal N. and Triggs B. (2005), "Histograms of oriented gradients for human detection," *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*. DOI: 10.1109/CVPR.2005.177
- [5] Giacomo C., Grazia L. Sciuto, Christian N., Emiliano T. and Marcin W. (2015) "Automatic Classification of Fruit Defects based on Co-Occurrence Matrix and Neural Networks," *Proceedings of the Federated Conference on Computer Science and Information Systems*, pp. 861-867.
- [6] Huertas A. and Medioni G. (1986), "Detection of Intensity Changes with Subpixel Accuracy Using Laplacian-Gaussian Masks," *IEEE Trans. On Pattern Analysis and Machine Intelligence*, Vol. 8, No. 5, pp. 651-664.
- [7] Itou M. (2014), "Defect Detection from Image Data Using Statistical Methods and Filter Processing," Bachelor Thesis, Department of Industrial Administration, Faculty of Science and Technology, Tokyo University of Science, (in Japanese).
- [8] Karasawa M. (2015), "Defect Detection from Image Data Using MT System," Bachelor Thesis, Department of Industrial Administration, Faculty of Science and Technology, Tokyo University of Science, (in Japanese).
- [9] Marr D. and Hildreth E. (1980), "Theory of Edge Detection." *Proceedings of the Royal Society of London. Series B, Biological Sciences*, Vol. 207, No. 1167, pp. 187-217
- [10] Md. T. Habib, Shaon B. Shuvo, Mohammad S. Uddin and F. Ahmed (2016), "Automated textile defect classification by Bayesian classifier based on statistical features," *2016 International Workshop on Computational Intelligence (IWCI)*. DOI: 10.1109/IWCI.2016.7860347
- [11] Sakai K (2010), "Introduction of Digital Image Processing," Tokyo: QC Press, (in Japanese).
- [12] Sano N., Mori Y. and Suzuki T. (2016), "Defect detection using two-dimensional moving range filter and unanimous vote among color component classifiers," *Proceedings of the 3rd Multidisciplinary International Social Networks Conference*. DOI:10.1145/2955129.2955137
- [13] Selvi M. and Jeneffa D. (2014), "Automated Defect Detection of Steel Surface Using Neural Network Classifier with Co-occurrence Features," *International Journal of Advanced Research in Computer Science and Software Engineering*, Vol. 4, No. 3, pp. 60-67.
- [14] Takagi M. and Shimoda Y. (2004), "Handbook of Image Analysis," Tokyo: University of Tokyo Press, (in Japanese).

- [15] Robert M. Haralick (1973), "Glossary and index of remotely sensed image pattern recognition concepts," *Partem Recognition*, Vol. 5, pp. 391-403.

Appendix

Table 5. Orthogonal table

No	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
	B	G	A	G	I	G	E	E	N	H	K	J	M	L	E	F	D×E	O	B×O	C	B×C	D×E	E×F	E×F	D	F×H	F×K	F×J	F×M	D×E	E×F
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
7	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
8	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
9	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
10	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
11	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
12	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
13	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
14	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
16	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
17	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
18	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
19	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
20	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
21	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
22	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
23	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
24	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
25	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
26	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
27	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
28	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
29	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
30	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
31	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
32	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Acknowledgements:

The authors would like to thank anonymous referees for their suggestions comments.

Author's biographical notes

Tatsuya Iwasawa is a graduate student at Department of Industrial Administration, Faculty of Science and Technology, Tokyo University of Science. His research has focused on statistical data analysis and statistical quality control.

Kenta Yoshida is a graduate student at Department of Industrial Administration, Faculty of Science and Technology, Tokyo University of Science. His research has focused on statistical data analysis and statistical quality control.

Natsuki Sano is an associate professor at Department of Economic Information, Faculty of Economic Information, Onomichi City University. His research has focused on applied statistics and data mining.

Mirai Tanaka is an assistant professor at Department of Industrial Administration, Faculty of Science and Technology, Tokyo University of Science. His research has focused on operations research and data analysis.

Tomomichi Suzuki is a professor at Department of Industrial Administration, Faculty of Science and Technology, Tokyo University of Science. His research has focused on statistical data analysis and statistical quality control.

[DOI : 10.17929/tqs.3.11]

Received: March 14, 2016

Revised: November 29, 2016

Accepted: April 5, 2017