Robust defect detection method for improving inspection process

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Abstract:
Automatic inspection machines for metal products can inspect products in large quantities and at a high speed while separating products without defects from defective products by using unified criteria. However, it is difficult to set accurate criteria to detect minute defects, and this results in misclassification. This study focuses on inspection techniques to improve the classification accuracy for an actual inspection process. There are differences in variables, such as raw materials, light color to capture images, and degree of degradation of light brightness, across different manufacturing plants. Previous studies utilized machine learning, image processing, and statistical methods. However, it is not clear how those different methods should be combined for improving the classification accuracy. Therefore, this study provides a comprehensive survey of an optimal combination of methods to increase robustness and improve classification accuracy. Furthermore, the results also suggest that a combination of methods can achieve classification accuracy and robustness exceeding those of previous methods.

Keywords
Image processing, Classification accuracy, Robust parameter design, Machine learning, Design of experiment

I. Introduction

Recently, 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 before. The use of automated inspection systems is increasingly essential in production lines to meet the growing demand for high quality production in a short duration. The use of automated inspection techniques is necessary at each level of production to improve the quality of production and to eliminate labor costs. However, for such online inspection machines, accurate criteria are required for distinguishing between the non-defective and defective products. Improper inspection criteria may allow defective products to be shipped, and the product quality would be degraded. In contrast, improper inspection criteria may also lead to disposing of good products, which cause wasted expense. Thus, it is necessary to determine proper inspection criteria to overcome the fore-mentioned limitations of online inspection machines. In these situations, automated inspection techniques for a specific type of metal product is of interest in which criteria of passing the inspection are strict because minute flaws, dirt, patterns, and dents are not allowed on the metal product.

Previous studies propose methods of defect detection on fabric surfaces (Chan and Pang., 2000; Mak et al., 2005; Stojanovic et al., 2001), glass plates (Chao and Tsai et al., 2008), and steel products (Arun et al., 2014). For example, Habib. et al. (2016) proposed a method to detect various defects in textile fabrics by using statistical techniques. Recently, machine learning algorithms were efficiently applied in several industries for the automatic detection of faults (Kang and Liu, 2005; Rimac-Drlje et al., 2005; Selvi et al., 2014). Capizzi et al. (2015) presented a new approach that classifies color and texture fruit surface defects by using machine learning. It should be noted that there are also research works for the products concerning in this paper. Karasawa (2015) improved classification accuracy by using Mahalanobis Taguchi methods that correspond to sophisticated distinction methods. However, it is still difficult to improve accuracy without appropriate preprocessing and feature extraction
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despite using the sophisticated methods. In order to address this issue, Sano et al. (2015) improved classification accuracy by using various preprocessing and feature-extraction methods. They succeed to combine several kinds of these methods, including feature quantity extraction window and texture characteristic quantity. However, the extent to which each method influences the classification accuracy as well as a way to optimally combine these methods to improve the classification accuracy remain unclear. Thereafter, recent studies focus on optimally combining these methods to achieve a better accuracy in order to improve classification accuracy (Iwasawa et al., 2016). Specifically, the study involved obtaining product pictures in a stationary state by using a research inspection machine with a single light color. The product was fabricated from two manufacturing plants that used different raw materials. Subsequently, they divided an inspection target range into three areas. Finally, they found the optimal combination of methods for each of those three areas and improve the classification accuracy. As another approach, Yoshida et al. (2016) proposed new methods to improve classification accuracy by combining two different machine learning methods to get a new adaptive method.

The major problems in previous studies can be summarized as follows:

1) Low robustness: The product used for inspection in this study is manufactured at several different manufacturing plants that use different raw materials. Moreover, while previous studies use single light color for a research inspection machine, each manufacturing plant uses different light colors. Therefore, the method proposed in a previous study (Iwasawa et al., 2016; Yoshida et al., 2016) was not effective for the products of all manufacturing plants and may not be suitable for other light colors that are used at each manufacturing plant. If inspection criteria are not unified for all the plants, each plant have to set inspection criteria. However, it is difficult to set proper inspection criteria for production lines with engineers who have less experience in quality management. This problem leads to low classification accuracy for these production lines.

2) Low classification accuracy: It is necessary to find an optimum combination including proposed methods of machine learning (Yoshida et al., 2016) and image processing (Iwasawa et al., 2016; Sano et al., 2015). Additionally, a unified optimum combination of methods is desired for all the three areas, so that it is convenient for actual production lines in different manufacturing plants.

3) Lack of blur correction and noise rejection methods: In previous studies, image blur correction is not considered. However, it is necessary to correct image blur for the products running on a production line in high-speed. Noise rejection methods are not introduced in the previous studies either. However, in order to apply for the actual production line, we need the effective noise rejection methods to improve the accuracy.

The aim of this paper is to propose a technique for determining the optimum combination of methods to increase robustness and improve classification accuracy. First, specific characteristics of the products and the process of creating data from the product images is described. This is followed by an overview of robust defect detection schemes to determine an optimum combination of methods to increase robustness and improve classification accuracy. Subsequently, an in-depth discussion of the experimental results is provided to combine the methods for increasing robustness and improving classification accuracy. Finally, the discussion is substantiated by verifying the power of robustness and classification accuracy with those of previous studies, and it is noted that the results in the present study correspond to the highest classification accuracy.

The remainder of this study is organized as follows. In Section II, we discuss the characteristics of the products and data extraction. In Section III, the experimental results are illustrated. In Section IV, the effectiveness of proposed method is shown. Finally, in Section V, we provide the conclusion of this research.

II. Creating data

Automated inspection systems distinguish between non-defective and defective products in a production line by using image data. Therefore, several studies (Chan and Pang, 2000; Mak et al., 2005, etc.) proposed new approaches based on image data. However, image data should not be handled directly because images for the study include backgrounds aside from an inspection target range to improve classification accuracy. Based on this, Figure 1 shows a method to create data. First, the inspection target range is extracted from the image data. Next, the inspection target range is converted into RGB values, which correspond to numerical values designating a specific 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 the eight-bit numbers. In order to facilitate defect detection, an HSL (hue, saturation, and lightness) range that unifies the three colors into a single RGB values used (Iwasawa et al., 2016). The HSL range is given by

\[ HSL = 0.299 \times R(i, j) + 0.587 \times G(i, j) + 0.114 \times B(i, j) \]

where \( (i, j) \) represent the row and column numbers, respectively. Dirt and dents are not allowed on non-defective products produced at a factory. However, the products may exhibit small patterns that appear similar to dents or dirt. To develop more stringent criteria, we analyze the labeled pseudo-defective sample products as training experiments.

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Sano et al. (2016) detected defects by analyzing the waveform data as opposed to directly analyzing rows and columns \((i,j)\) of the matrix data. The characteristic waveforms are also examined to detect the defects. Figure 2 shows the waveform for an average product height (i.e., the average of a row of the matrix data). Figure 2 shows a relatively large sample of a given defect that contains high and low points. The waveform suddenly dips near row 470 because of the defects. The defects are identified by the sudden changes of the numerical values as opposed to the average maximum or minimum. In this case, detection of small defects is difficult because such defects cause small changes in the numerical values.
products are $T_1$ and $T_2$ respectively, and the judged state are $y_1$ and $y_2$. The probability of discriminating $y_j$ in the true state of $T_i$ is $p_{ij}$. For example, the probability a defective product is erroneously determined as a non-defective product is $p_{21}$. A signal-to-noise ratio for binary input-output system,

$$\eta = -10 \log \left[ \frac{1}{(1 - 2p_0)^2} - 1 \right],$$  

(1)

is proposed as a measure to quantitatively evaluate performance, where

$$p_0 = \frac{1}{1 + \sqrt{\theta}}$$  

(2)

is the estimated common error rate, and

$$\theta = \frac{p_{11}p_{22}}{p_{12}p_{21}}$$  

(3)

is the sample odds ratio. Therefore, A signal-to-noise ratio for binary input-output system is an evaluation measure that takes into consideration errors of type I error and type II error. In order to apply different raw materials in several manufacturing plants, almost identical amounts of products are collected from the several manufacturing plants, and this corresponds to the sum of 531 products.

Table 1. Assignment of control factors, uncontrollable factors, and indicative factors.

| Control factors | Uncontrollable factors | Indicative factor |
|----------------|------------------------|-------------------|
| Symbol | Factor | Methods | Parameter | Level | Level Position | Lightness |
| | | | Parameter | | | |
| A | Non linear density conversion | Not use / Use | Not use | 1 | No shift | Bright |
| B | Richardson–Lucy deconvolution | Size of PSF | 2 | 2 | 4 |Bright |
| C | | Number of iterations | 1 | 1 | 5 | 10 |
| D | Guided filter | Size of square window | 6 | 6 | 9 | 12 |
| E | | Regularization parameter | 0.01 | 0.01 | 0.1 | 0.2 |
| F | Laplacian filter | Size of neighbour | Not use | Not use | 4 | 8 |
| G | Operation of the row | Statistics | Variance | Maximum | Standard deviation |
| H | One difference | Number of lags | 1 | 5 | 10 |
| I | Feature quantity extraction with window | Size of window | 5=1 | 5=1 | 15=1 | 25=1 |
| J | AdaBoost-applied neural networks | Number of hidden units | 1 | 1 | 3 | 5 |
| K | | Regularization parameter | 0.005 | 0.010 | 0.015 |
| L | | Number of weak classifiers | 100 | 100 | 300 | 500 |

With respect to the control factors, Symbols A, F, G, H, and I were introduced in a previous study (Iwasawa et al., 2016), and Symbols J, K, and L were introduced by Yoshida et al. (2016). The first-level factor corresponds to “Used,” and the second-level factor corresponds to “Not used.” This method is selected to perform an experiment if the first level is selected. This method is not used to perform an experiment if the second level is selected. Generally, optimum parameters for symbol J, K and L are determined by Grid search. In this study, in order to determine optimum parameters by investigating the tendency of factorial effect graphs, we assign symbol J, K and

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Las control factors. In the production line, the automatic detection system captures a product picture because the center of the product is located in the center of image. However, it is difficult for an automatic detection system to obtain the center of the product when the product is associated with a high speed. Therefore, it is difficult for an automatic detection system to distinguish between non-defective and defective products when images are used in which the center of the product is not located in the center of an image. Lights for the automatic detection system are changed once every few years in a manufacturing plant. Images are brighter than previous images when the lights are just changed. Conversely, images become darker when the lights are used for several years, and this leads to a decrease in the classification accuracy. In order to obtain darker images, two uncontrollable factors are set that can influence classification accuracy. Moreover, each of the several manufacturing plants have introduced one light color from three. Hence, three light colors are set as an indicative factor.

B. Richardson-Lucy deconvolution

In order to ensure a high speed and mass production line, an automatic inspection machine must include a short calculation period and a high blur correction method. Currently, several high blur correction methods are proposed because the camera market demands higher levels of technology. For example, Nayar et al. (2004) proposed a high blur correction method for motion blurs. This method is applicable to indoor and outdoor scene images. However, these high blur correction methods require a lengthy calculation time, and thus they are not applicable for a high-speed production line. In the blur correction field, several studies, such as Chan et al. (1998), use the advantage of the point spread function (PSF) of the system that corrects blur because of the effectiveness and simplicity of the algorithm. Thus, the “Richardson-Lucy deconvolution (RLD)” method is introduced in the present study since it requires a short calculation time and uses PSF (Biggs et al. 1997). The image degradation is modeled as follows:

\[ g = h \otimes f + n, \]  
(4)

where \( f \) denotes the original undistorted image, \( g \) denotes distorted noisy image, \( h \) denotes the PSF of the system that uses a square window with a radius \( r \), \( \otimes \) denotes the convolution operator, and \( n \) denotes the corrupting noise. Specifically, \( r \) indicates the number of pixels that are blurred. The iterative RLD algorithm is given as follows:

\[ \hat{f}_{k+1} = \hat{f}_k \left( h \ast \frac{g}{h \otimes \hat{f}_k} \right), \]  
(5)

where \( \hat{f}_k \) denotes the estimate of \( f \) after \( k \) iterations, and \( \ast \) denotes the correlation operator. The images are restored to blur corrected images when \( r \) and \( k \) parameters are accurately set. In order to improve the ease of blur corrected images and defect detection, three level parameters are assigned to Symbols B and C in Table 1 to explore the optimum parameters.

C. Guide image filter

It is essential to introduce effective noise rejection methods for easy defect detection to apply an actual line in which an image includes a low amount of noise. Previous studies (Iwasawa et al., 2016; Yoshida et al., 2016) introduced a Gaussian filter that used filter processing and involved a short calculation time. However, it is easy to use Gaussian filters to reduce edges in an image because it is not possible to adjust the parameter for a smoothing degree. In a previous study, the removal of noise beyond a necessary level leads to the reduction of edges that correspond to defect points in an image. Therefore, the use of a Gaussian filter makes it more difficult for defect detection as opposed to not using it. A guided filter (Sun et al., 2013) is introduced with good edge-preserving smoothing properties although it is possible to adjust the parameter for easy defect detection. It is assumed that \( q \) is a linear transform of \( p_i \) in a window \( \omega_k \) centered at the pixel \( k \) as follows:

\[ q_i = a_i p_i + b_i, \quad \forall i \in \omega_k \]  
(6)

where \( (a_k, b_k) \) denote linear coefficients that are assumed as constant in \( \omega_k \). A square window of a radius \( r \) is used, and \( a_k \) and \( b_k \) are given as follows:
\[ a_k = \frac{\sigma_k^2}{\sigma_k^2 + \varepsilon}, \quad (7) \]

\[ b_k = (1 - a_k)\mu_k. \quad (8) \]

Here, \( \mu_k \) and \( \sigma_k^2 \) denote the mean and variance of \( \omega_k \), respectively, and \( \varepsilon \) denotes a regularization parameter that penalizes a high \( a_k \). In order to solve (1), \( \bar{a}_i \) and \( \bar{b}_i \) are given as follows:

\[ \bar{a}_i = \frac{1}{|\omega|} \sum_{k \in \omega_i} a_k, \quad (9) \]

\[ \bar{b}_i = \frac{1}{|\omega|} \sum_{k \in \omega_i} b_k. \quad (10) \]

It is necessary to appropriately set the two parameters \( \varepsilon \) and \( r \) while introducing a guided filter to remove noise. Therefore, three level parameters are assigned to Symbols D and E in Table 1 to explore the optimum parameters.

**D. Experimental result**

The optimal level for each control factor is selected to construct an optimal combination of methods by using classification accuracies and signal-to-noise ratios for a binary input-output system. The summation of four level uncontrollable factors, three indicative factors, and three areas results in 36 factorial effect graphs for classification accuracies and signal-to-noise ratio. In this experiment, classification accuracies are measured by using 3-fold cross validation. Most factorial effects for classification accuracies are not high although there are a few high factorial effects for signal-to-noise ratio. Therefore, the optimal level for each control factor is selected based on factorial effects for signal-to-noise ratio. In order to understand the tendency of each factorial effect, an example of the factorial effects for the K1N1 level is shown in Figure 3.

The tendency of factorial effects for each area is almost identical across the 36 results. Therefore, a unified method to increase robustness is determined by selecting an optimum level for each method. The selected optimum levels for each symbol are shown in Table 2. The optimum levels of Symbols A, C, F, and I are identical across the 36 results. The optimum levels of Symbols B, D, G, J, K, and L are slightly different across the 36 results although most of factorial effects are identical. Thus, it is easy to select optimum levels for the fore-mentioned five Symbols. However, it is difficult to select optimum levels for Symbols E and H due to differences across areas, uncontrollable factors, and indicative factors of factorial effects. Specifically, discrimination in area2 is the most difficult because this area is noisier and involves darker images when compared to other areas. In order to increase robustness and improve classification accuracy for area2, the study focuses on improving the signal-to-noise ratio for area2 and selects the optimum level for Symbols E and H as specified. With respect to the 36 results, the factorial effects for Symbols C, D, and F exceed those of the other Symbols. Previous studies do not focus on blur correction and noise rejection methods. Thus, in the present study, RLD and guided filter are introduced and applied for an actual production line. The setting of an appropriate parameter is expected to increase robustness and improve classification accuracy because of the large factorial effects for Symbols C and D.

**Table 2. Optimum levels for each symbol.** Optimum levels and parameters are selected from Table 1.

| Symbol | A | B | C | D | E | F | G | H | I | J | K | L |
|--------|---|---|---|---|---|---|---|---|---|---|---|---|
| Optimum level | 1,3 | 3 | 1 | 2 | 1 | 1 | 3 | 1 | 2 | 2 | 3 | 3 |
| Optimum parameter | Not use | 6 | 1 | 9 | 0.01 | Not use | Standard deviation | 1 | 15×1 | 3 | 0.015 | 500 |

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Figure 3. Factorial effect graphs for the signal-to-noise ratio for K1N1 level.

IV. Discussion

This section discusses as to whether proposed method that selects the optimum level in the experiment described in Section III increases robustness and improve classification accuracy when compared to those of previous studies. The results obtained in the present study for the optimal combinations of methods are compared with those of a previous method (Iwasawa et al., 2016) that displayed the highest accuracy among all methods proposed in extant studies. The fore-mentioned study divided a product into three areas and used different methods for each area. Thus, the method calculated three accuracies for each area by using three different methods. In contrast, the method proposed in the current study calculated three accuracies by using a single method. Additionally, the aim of the present study involved applying three light colors given that the several manufacturing plants used lights that are different from each other. Therefore, it is necessary to confirm that the robustness of the proposed method can be applied for three light colors and to also compare accuracies for three lights with those in the previous study as shown in Table 3. Specifically, 240 non-defective and 240 defective products are prepared for each area. Thus, there are 480 products for area1, area2, and area3.

Table 3. A comparison of classification accuracies obtained by using a method used in a previous study and the optimal combination of methods proposed in the present study. Classification accuracy is calculated for each area and light colors.

| Method         | Area1  | Area 2 | Area 3  |
|----------------|--------|--------|---------|
|                | Color A | Color B | Color C | Color A | Color B | Color C | Color A | Color B | Color C |
| Proposed method (a) | 73.50%  | 76.00%  | 71.70%  | 65.00%  | 71.20%  | 76.90%  | 84.60%  | 78.10%  | 82.90%  |
| Previous method (b) | 72.08%  | 76.88%  | 67.92%  | 69.79%  | 73.33%  | 75.62%  | 75.21%  | 56.46%  | 72.50%  |
| Difference (a) - (b) | 1.42%  | -0.88%  | 3.78%   | -4.79%  | -2.13%  | 9.39%   | 21.64%  | 10.40%  |

In this study, an optimal combination of methods is constructed to increase robustness and improve classification accuracy. This is different from previous studies that focus on improving accuracy. The results
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indicate that the proposed method displays robustness and maintains high accuracies for all light colors and areas. Additionally, with respect to all areas, accuracies for the proposed method with Color A, Color B and Color C correspond to 9.39%, 21.64% and 10.40%, respectively, and are higher than those in previous studies. The accuracy of the Color B in the method proposed in the previous study corresponds to 55% and is considerably low. However, its accuracy for the method proposed in the present study is significantly higher. This indicated that the method proposed in the present study increases robustness and improve classification accuracy.

V. Conclusion

In this paper, we proposed a novel technique for determining optimum combinations of methods to increase robustness and improve the classification accuracy for metal products via their image data. The technology is applicable for the images of different raw materials, taken under different light illumination, and possibly with dislocation and the defect position. Moreover, even for blur and noisy images, the optimum combinations of methods perform high classification accuracy, because blur correction and noise rejection methods are also taken in mind to defect detection. In particular, the accuracy of “Color B area3” was quite unsatisfactory in the previous studies, and the accuracies and robustness of our methods are significantly higher.

As our further study, it is supposed to further improve the classification accuracy. Accordingly, we intent to simultaneously consider some recently developed machine learning methods and our approach, such as the methods introduced by Capizzi et al. (2015) for automatic inspection system for detecting minute defects.

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