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Automated recognition of surface defects using digital color image processing

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Abstract

One of the computerized technologies for advanced infrastructure inspection methods is the application of digital image processing. Digital image processing methods have been developed for steel bridge coating inspections for the past few years. The rust percentages on steel bridge coating surfaces can be reliably computed through the use of digital image processing methods. However, previous researchers solely focused on the determination of the degree of rust defects on the steel surfaces in percentage. Therefore, an automated processor that can recognize the existence of bridge coating rust defects needs to be developed. This paper presents the development of a rust defect recognition method to determine whether rust defects exist in a given digital image by processing digital color information. For the development of the image processor, color image processing is employed, instead of grayscale image processing commonly used in previous researches, since rust defects are distinctive in color against background.

Keywords: Steel bridge coating; Rust defect recognition; Color image processing

1. Introduction

Deteriorating infrastructure systems, insufficient budget amounts, and increasing public demand for safer transportation systems have motivated federal/state agencies to find more objective and computerized infrastructure inspection methods [1]. Conventional inspection methods consist of visual inspections by inspectors. While a careful visual inspection can provide valuable information, it has inherent limitations in identifying the structural integrity and assessing the level of damage of a facility. Inspectors cannot access every part and space of infrastructure. Therefore, many problems can be neglected until they become serious and require costly repair.

One of the computerized technologies for advanced infrastructure inspection methods is the application of digital image processing. Digital image processing methods have been developed for steel bridge coating inspections for the past few years. The rust percentages on steel bridge coating surfaces can be reliably computed through the use of digital image processing methods. However, most researches solely focused on the calculation of the degree of rust defects on the steel surfaces in percentage. Therefore, an automated processor that can recognize the existence of bridge painting rust defects needs to be developed. Once this processor is created, it can be combined with the processor for calculating the degree of rust defects. In other words, the integrated system for coating surface condition assessment can be developed with two image processors equipped: the pre-processor and the main processor. The pre-processor is required to check whether a given digital image contains defective parts. If the image is judged as defective, the image is sent to the next stage, the main processor, to make an accurate defect assessment.

In the civil engineering domain, not much research was performed for defect recognition using digital images. Many examples can be found in pavement areas [2–4]. Those previous research studies focused on the recognition of pavement cracks and the classification of crack types applying the projection method. This method projects the intensity

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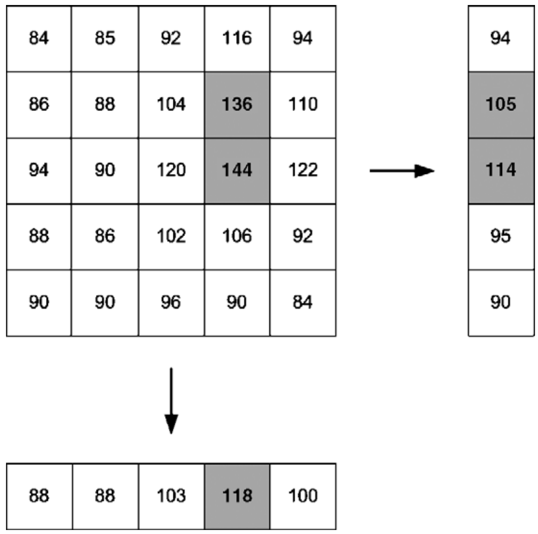

Fig. 1. Projection method.

values of a grayscale image horizontally and vertically. Fig. 1 shows an example of the projection method using a 5 by 5 pixel digital image. The numbers in each pixel indicate the light intensity values where 0 means white and 255 means black. Two pixels with darker areas are defective areas, showing high intensity values. The horizontal projection map can be generated by averaging the sum of each row pixel values. Likewise, the vertical projection map can be obtained by averaging the sum of each column values. The existence of defective areas can be identified by comparing pixel values in the horizontal and vertical projection maps.

This method seems to be effective for the defects whose types have a long linear shape such as pavement cracks. However, bridge painting rust defects are often characterized as small scattered spots. In addition, coating surfaces experience non-uniform illuminations and noises arising from foreign materials. Such factors can cause non-defective images to be classified into defective images from the use of the projection method. Therefore, this article proposes a novel approach to recognize the existence of bridge coating rust defects by processing digital color images for statistical data acquisition and performing a multivariate statistical analysis.

2. Research methodology

The methodology for the development of a rust defect recognition method, called the RUDR method hereinafter, can be classified into four stages: data preparation, data analysis, statistical modeling, and testing and validation. Fig. 2 shows

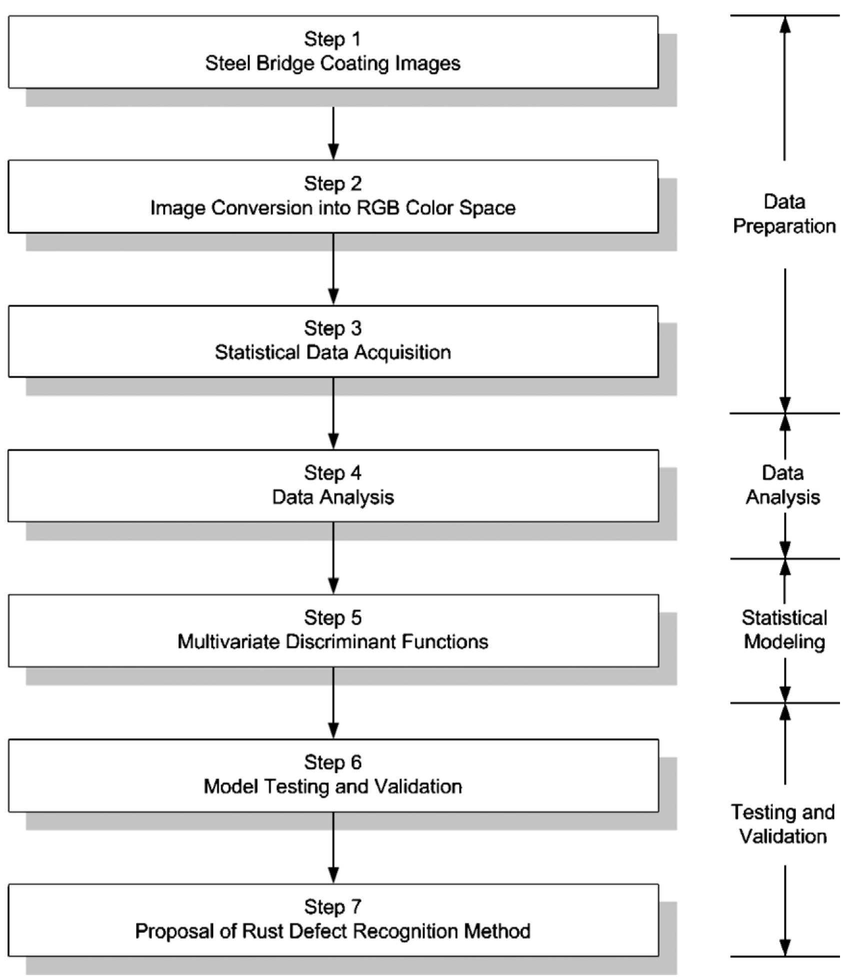

Fig. 2. Research methodology for rust defect recognition method.

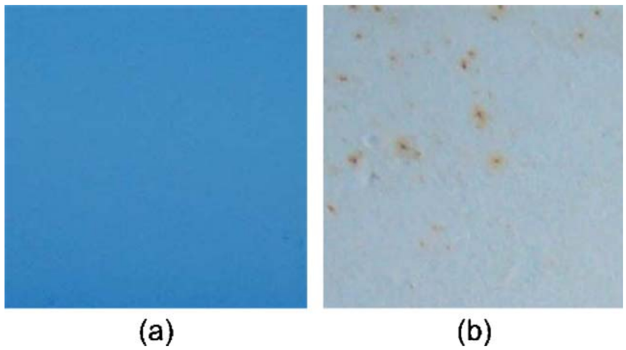

Fig. 3. Illustrative bridge coating images ((a) non-defective image; (b) defective image).

the whole research steps for the image processor that are sequentially linked together. The detailed description of each stage is given as follows.

In the data preparation stage, steel bridge coating images have to be taken first. For this task, total 20 highway steel bridges on the Interstate Highway 65 were visited on September 1, 2004 and those bridges were coated with blue paint, one of the most commonly used painting colors. During the data acquisition with a digital camera, bridge coating images were taken at a distance of around 3 ft from the steel beam surfaces to acquire clearer coating images and kept at a right angle. Image data sets were generated from the acquired coating images. Two kinds of data sets need to be created: a defective group and a non-defective group. In this research, 30 digital images from each group are used for statistical data generation and multivariate statistical modeling. For defective group generation, only the images containing tiny to small rust defects are used for increasing model efficiency. One of the purposes to develop this model is to facilitate preventive maintenance where defects in initial status have to be detected efficiently. Also, large defects generally can be easily detected and detecting them is not a critical matter if small defects are detected clearly. Fig. 3 shows the example of defective and non-defective painting images. Then, the images from each group are converted to scatter plots on the RGB (Red, Green, and Blue) color space that is the most fundamental color space. From the scatter plots, a number of statistical data or variables are extracted for further processing.

In the data analysis stage, collected variables are analyzed to narrow down the number of variables for modeling. The ultimate goal of the development of RUDR method is to develop multivariate discriminant functions to classify non-defective images into a non-defective group and defective images into a defective class. To create such functions, the variables have to be first analyzed to see if they have a significant impact to the functions. In this research, the variables pass through two kinds of analyses: the Wilks' lambda analysis and the data range analysis. From these two tests, significant variables or discriminating variables are determined.

In the statistical modeling stage, multivariate discriminant functions are created using the variables carefully chosen in the previous stage. The discriminant functions can be expressed as a linear combination of discriminating variables as follows.

$$f(x) = b_1x_1 + b_2x_2 + \ldots + b_nx_n + c \qquad (1)$$

where, b_i is a discriminant coefficient, x_i is a discriminating variable, and c is a constant. There are two main purposes for using discriminant functions [5]:

1) To find a rule to separate distinct sets of objects from several known populations with a few discriminating variables as much correctly as possible;
2) To predict the classes where new objects will be assigned by using the previously derived rule.

In the testing and validation stage, the developed statistical model is tested and validated with new bridge painting images. Model efficiency for the recognition of rust defects will be identified.

3. Image data preparation

3.1. Image conversion

For the exploration of RUDR method, bridge painting images were prepared and divided into two groups: non-defective and defective. Each group has 30 digital images for data acquisition. The images are expressed as the most fundamental color space, the RGB color space. The color space, expressed as cube, has three primary colors: red, green, and blue as shown in Fig. 4 [6]. Each primary color axis has 256 (2^8) levels of color shade, which means a total of 2^{24} colors can be generated from the color space.

The origin of the cube corresponds to black and the point with (1,1,1) indicates white. The three primary colors of red,

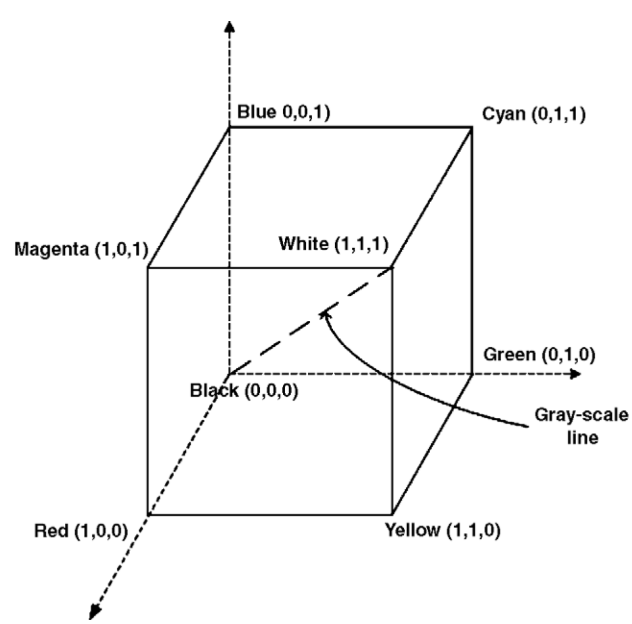

Fig. 4. RGB color space.

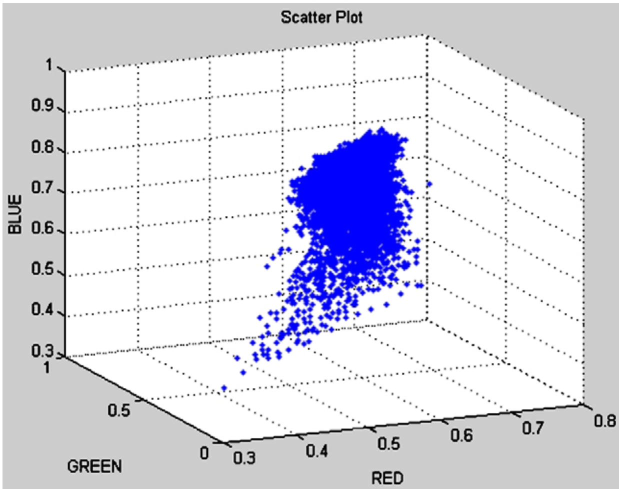

Fig. 5. Image conversion to scatter plot.

green, and blue are located on each primary axis. If three primary colors are added together at full intensity (1,1,1), the color white can be generated. The line connecting black and white is called a gray-scale line, on which every point represents gray colors with different intensities.

For the statistical data generation, bridge painting images are converted into scatter plots of RGB color space as shown in Fig. 5. Scatter plots showing the distribution of three color values have a different shape depending on coating images, a characteristic of which may play an important role in differentiating non-defective images from defective images.

3.2. Statistical data acquisition

In this step, a number of statistical data are extracted from the scatter plot of a coating digital image. Three descriptive statistic values are selected to characterize the shape of the plot. They are: difference (DIFF), mean (MEAN), and standard deviation (STD). The variable of DIFF means the difference between a maximum value and a minimum value that means the range of the data. To acquire statistic values of three color channels, scatter plots have to be projected to each primary axis. Then, three statistical variables are calculated from a digital image for the three color channels, totaling nine variables from one image. Fig. 6 shows the statistical data acquisition process schematically.

The variables can be calculated from the following equations.

$$\max(i) = \max(x_{ij}) \tag{2}$$

Where, i (color channels) = red, green, or blue j (number of pixels in an image) = 1, 2,. . ., n

$$\min(i) = \min(x_{ij}) \tag{3}$$

$$\mathrm{DIFF}(i) = \max(i) - \min(i) \tag{4}$$

$$\mathrm{MEAN}(i) = \overline{x_i} = \frac{1}{n}\sum_{j=1}^{n} x_{ij} \tag{5}$$

$$\mathrm{STD}(i) = s_i = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}\left(x_{ij} - \overline{x_i}\right)^2} \tag{6}$$

4. Data analysis

The collected data are analyzed to choose discriminating variables that are significant for the separation of two or more groups. For the purpose of selecting efficient variables, two

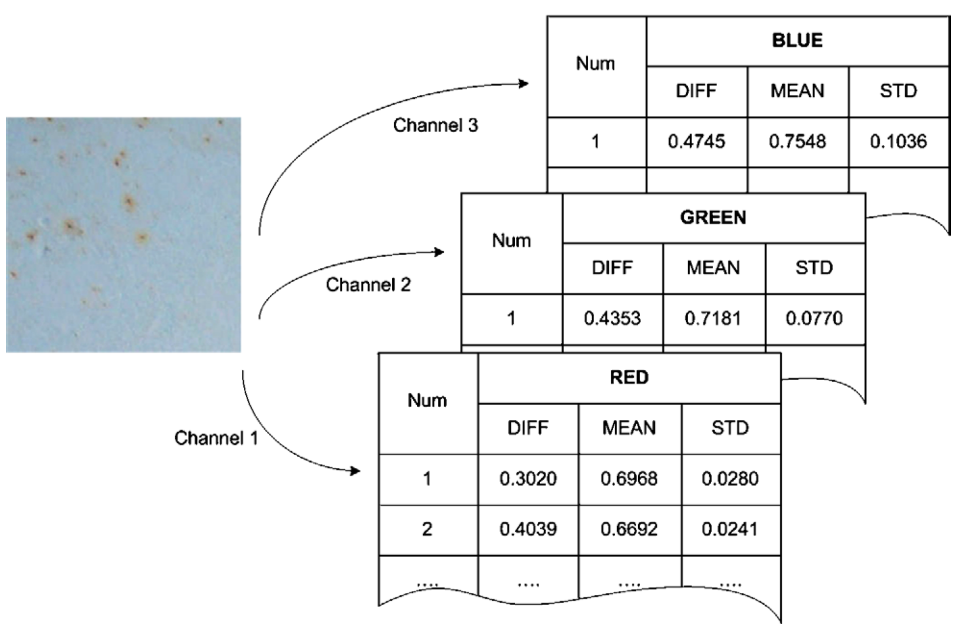

Fig. 6. Statistical data acquisition.

kinds of analyses are performed: Wilks' lambda analysis and data range analysis.

4.1. Wilks' lambda analysis

The Wilks' lambda analysis is a quantitative method to test mean differences between two or more groups. The greater the difference in mean values of a variable between two groups, the more that variable can contribute to discriminant functions. The degree of the contributions is measured as the lambda that varies from 0 to 1. The smaller lambda for a variable means the variable contributes more to the discriminant functions. And, the larger lambda implies the variable contributes less to the functions. In other words, group means are close together. The lambda of 1 means all group means are the same. The Wilks' lambda can be obtained from the relation between a within-group variability and a between-group variability [7,8].

The equation for the Wilks' lambda is as follows.

$$\Lambda = \frac{\mathrm{SSwg}}{\mathrm{SSbg} + \mathrm{SSwg}} \tag{7}$$

Where,
SSwg = sum of squares within-groups or within-group variability
SSbg = sum of squares between-groups or between-group variability

These two values are calculated as follows:

$$\mathrm{SSwg} = \sum_{i=1}^{k} \sum_{j=1}^{n_i} \left(x_{ij} - \overline{x_i}\right)^2 \tag{8}$$

Where
k = number of groups
n_i = number of observations in each group
$\bar{x}_i$ = group mean
and

$$\mathrm{SSbg} = \sum_{i=1}^{k} n_i(\overline{x_i} - \bar{x}\ )^2 \tag{9}$$

Where, $\bar{x}$ = total mean

The lambda values were calculated for the nine variables from the three color channels. Table 1 shows the calculation results of SSwg, SSbg, and Λ, respectively. Lambda values of the variables have a wide variation ranging from 0.0878 to 0.9419. Three variables feature very low lambda values. They are: MEAN in red, DIFF in green, and DIFF in blue. Among them, the DIFF in blue has the lowest value, 0.0878. The variables of STD in red and MEAN in blue formulate the largest lambda value group, which means both variables make a weak contribution to the separation of two groups, defective and non-defective.

Table 1
Lambda values of variables

Variable		SSwg	SSbg	Λ
Red	DIFF	0.4595	0.9845	0.3182
	MEAN	0.3058	2.0236	0.1313
	STD	0.0022	0.0001	0.9419
Green	DIFF	0.3922	2.1407	0.1548
	MEAN	0.1447	0.3176	0.3130
	STD	0.0076	0.0023	0.7670
Blue	DIFF	0.3291	3.4184	0.0878
	MEAN	0.1195	0.0080	0.9371
	STD	0.0176	0.0120	0.5934

Based on the calculated group variances, F statistical testing was performed to examine the statistical significance of all variables. The formula for F statistic is as follows [9].

$$F = \frac{\mathrm{SSbg}/df_{\mathrm{BG}}}{\mathrm{SSwg}/df_{\mathrm{WG}}} \tag{10}$$

Where
SSwg : sum of squares within-groups or within-group variability
SSbg : sum of squares between-groups or between-group variability
df_{BG} : degrees of freedom of between-group variability
df_{WG} : degrees of freedom of within-group variability

The formulas for computing degrees of freedom are as follows.

$$df_{\mathrm{BG}} = k - 1 \tag{11}$$

$$df_{\mathrm{WG}} = N - k \tag{12}$$

Where,
k = number of groups
N = total number of observations

Then, the computed F statistic is compared with critical values to examine if the Fstatistic is sufficiently larger than critical values. If the F statistic is large enough, it means group means are unequal. The critical value at the 95% confidence level is used in this study. Regarding the selection of the critical value, [9] mentions that a 95% confidence level is adequate in most research situations and 99% or higher confidence levels may be utilized when important decisions about human beings are made. The critical value is:

$$F_\alpha(df_{\mathrm{BG}}, df_{\mathrm{WG}}) = F_\alpha(k-1, N-k) = F_{0.05}(1, 58) = 4.01 \tag{13}$$

From the Eqs. (10) and (13), a threshold lambda value for testing if group means are equal can be drawn.

$$\frac{\mathrm{SSbg}/1}{\mathrm{SSwg}/58} = F_{0.05}(1, 58) = 4.01 \tag{14}$$

By inserting the SSbg into Eq. (7),

$$\Lambda = \frac{\mathrm{SSwg}}{\mathrm{SSbg} + \mathrm{SSwg}} = \frac{\mathrm{SSwg}}{\frac{4.01}{58}\mathrm{SSwg} + \mathrm{SSwg}} = 0.93 \tag{15}$$

Therefore, if the lambda value of a variable is more than 0.93, the group means of the variable are equal at the 95% confidence level and the variables are eliminated from the consideration of discriminating variables. From Table 1, the variables of STD in red and MEAN in blue have lambda values more than 0.93 and the other variables have lambda values less than the threshold value, which implies group means are different at the 95% confidence level.

Even if the F statistical testing found that group means of seven variables are significantly different, the variables are still too many to develop discriminant functions because the functions are a statistical method to separate two populations with a few variables. Thus, another analysis, a data range analysis, is performed to minimize the number of significant variables.

4.2. Data range analysis

This analysis is a method to present the ranges of statistical data of three color channels. Then, by comparing the ranges of a defective group and a non-defective group, the most significant variable from each color channel can be determined. For instance, if the ranges of a variable between two groups are overlapped too much, the variable cannot have a significant impact to the separation of the two groups. Otherwise, the variable can be considered as an important factor to discriminate two populations. For the systematic comparison, the measure for the degree of overlap (DO) can be drawn as follows and Fig. 7 shows the meaning of values in the equation.

$$\mathrm{DO} = \frac{\min(a_\mathrm{h}, b_\mathrm{h}) - \max(a_\mathrm{l}, b_\mathrm{l})}{\max(a_\mathrm{h}, b_\mathrm{h}) - \min(a_\mathrm{l}, b_\mathrm{l})} \tag{16}$$

Where, $-1 < \mathrm{DO} \leq 1$
a_l, b_l = lowest value of each data range
a_h, b_h = highest value of each data range

The DO value varies from -1 to 1 where positive DO values mean the data ranges of two groups intersect in part and negative DO values indicate the data ranges of two groups never intersect each other. Table 2 shows the data ranges of two different groups in terms of red, green, and blue channels. In this analysis, a total of seven variables are considered since two variables, STD in red and MEAN in blue, are discarded in the previous analysis.

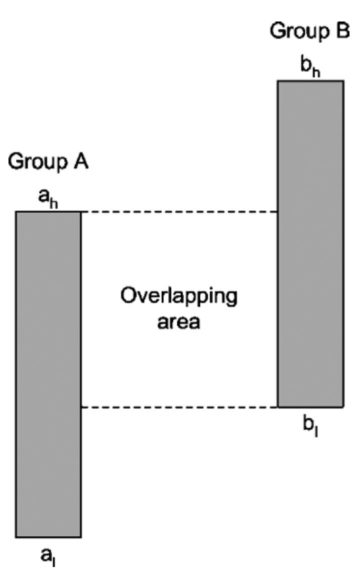

Fig. 7. Degree of overlap.

Table 2
Data ranges of seven variables

Color	Group	Variable	High	Low
RED	Non-defective	DIFF	0.2706	0.0667
		MEAN	0.4601	0.1873
	Defective	DIFF	0.6941	0.2036
		MEAN	0.7711	0.5726
GREEN	Non-defective	DIFF	0.2902	0.0549
		MEAN	0.6876	0.4531
		STD	0.0458	0.0056
	Defective	DIFF	0.6941	0.3373
		MEAN	0.7774	0.6234
		STD	0.0770	0.0156
BLUE	Non-defective	DIFF	0.3608	0.0588
		STD	0.0600	0.0077
	Defective	DIFF	0.7529	0.4745
		STD	0.1036	0.0240

Fig. 8 shows the DO values and their bar chart in terms of the seven variables. The comparison reveals the most significant variable from each color channel. The variables are: MEAN in red, DIFF in green, and DIFF in blue. They all produced negative DO values which mean two groups, defective and non-defective, can be differentiated very well by the three variables. Therefore, based on the consistency between the Wilks' lambda analysis and the data range analysis, three variables are selected for the development of discriminant functions. They are: MEAN in red (RMEAN), DIFF in green (GDIFF), and DIFF in blue (BDIFF).

5. Multivariate discriminant functions

Multivariate discriminant functions are a very useful method to separate two or more classes or populations and assign a new observation to one of two or more classes. To model successful discriminant functions, appropriate variables have to be selected on the basis of a number of measurements. The examples applying the discriminant functions can be found in many areas [5]. They include: purchasers of new products and those to purchase slowly, successful or unsuccessful college students, medical disciplines to predict serious diseases like cancer, good and poor credit status, alcoholics and nonalcoholics, and more.

In this research, discriminant functions are utilized for the creation of RUDR method and three major variables were determined in the previous stage. [5] presented discriminant functions considering minimum misclassification cost. The equation is for two populations and the populations are assumed to be multivariate normal densities. In many statistical analyses, populations can be assumed to be normal because of simplicity of problem solution and reasonably high efficiency.

If there are two populations, π_1 and π_2, and the number of sampled data of p random variables is n_1 and n_2, respectively,

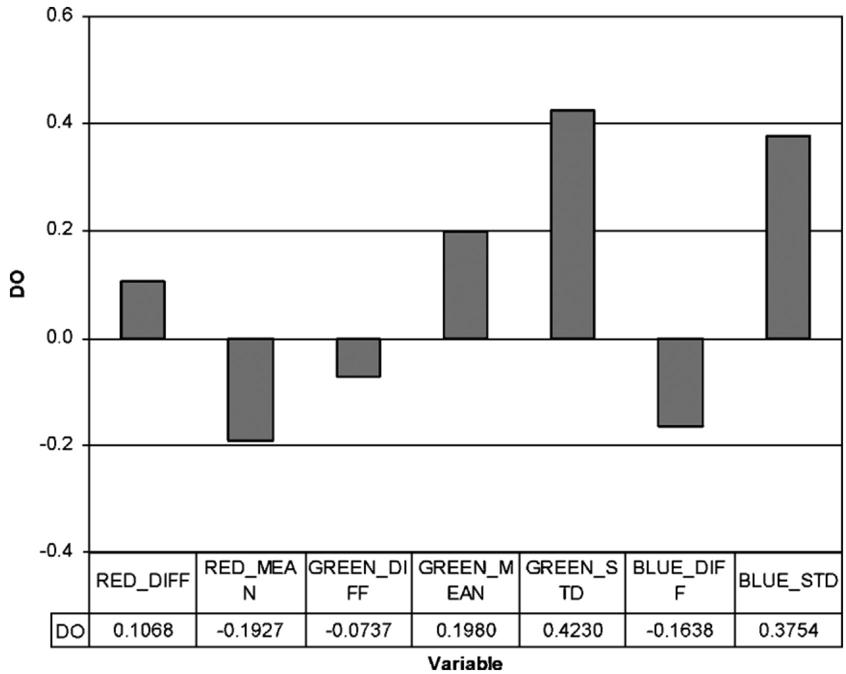

Fig. 8. DO (degree of overlap) values of seven variables.

sample mean vectors ($\overline{x_1}$) and covariance matrices (S_i) are defined as follows.

$$\underset{(p\times 1)}{\overline{x_1}} = \frac{1}{n_1}\sum_{j=1}^{n_1} x_{1j} \tag{17}$$

$$\underset{(p\times p)}{S_1} = \frac{1}{n_1-1}\sum_{j=1}^{n_1}\left(x_{1j}-\overline{x_1}\right)\left(x_{1j}-\overline{x_1}\right)^T \tag{18}$$

$$\underset{(p\times 1)}{\overline{x_2}} = \frac{1}{n_2}\sum_{j=1}^{n_2} x_{2j} \tag{19}$$

$$\underset{(p\times p)}{S_2} = \frac{1}{n_2-1}\sum_{j=1}^{n_2}\left(x_{2j}-\overline{x_2}\right)\left(x_{2j}-\overline{x_2}\right)^T \tag{20}$$

Where, T=vector transposition

For simplicity, the above sample covariance matrices are assumed to be the same. Then, one combined or pooled covariance matrix can be derived as follows.

$$S_{\text{pooled}} = \left[\frac{n_1-1}{(n_1-1)+(n_2-1)}\right]S_1 + \left[\frac{n_2-1}{(n_1-1)+(n_2-1)}\right]S_2 \tag{21}$$

The discriminant function for two normal populations is defined as follows.

The new observation of x_0 is allocated to π_1 if

$$\left(\bar{x}_1-\bar{x}_2\right)^T S_{\text{pooled}}^{-1}x_0 - \frac{1}{2}\left(\bar{x}_1-\bar{x}_2\right)^T S_{\text{pooled}}^{-1}\left(\bar{x}_1-\bar{x}_2\right) \geq \ln \times\left[\left(\frac{c(1/2)}{c(2/1)}\right)\left(\frac{p_2}{p_1}\right)\right] \tag{22}$$

Where,

p_1, p_2 =prior probability

$c(1/2)$ =cost when an observation from π_2 is misclassified as π_1

$c(2/1)$ =cost when an observation from $\pi_1$is misclassified as π_2

The cost functions and prior probabilities in the above equation can be assumed as equal to each other. Then, the above function can be simplified as follows.

$$\left(\bar{x}_1-\bar{x}_2\right)^T S_{\text{pooled}}^{-1}x_0 - \frac{1}{2}\left(\bar{x}_1-\bar{x}_2\right)^T S_{\text{pooled}}^{-1}\left(\bar{x}_1-\bar{x}_2\right) \geq 0 \tag{23}$$

Returning to this research, sample mean vectors of non-defective (π_1) and defective (π_2) classes are prepared according to Eqs. (17) and (19). Those are:

$$\overline{x_1} = \begin{bmatrix}\text{RMEAN}_1\\ \text{GDIFF}_1\\ \text{BDIFF}_1\end{bmatrix} = \begin{bmatrix}0.3422\\ 0.1238\\ 0.1318\end{bmatrix} \tag{24}$$

$$\overline{x_1} = \begin{bmatrix}\text{RMEAN}_2\\ \text{GDIFF}_2\\ \text{BDIFF}_2\end{bmatrix} = \begin{bmatrix}0.7095\\ 0.5016\\ 0.6091\end{bmatrix} \tag{25}$$

And, covariance matrices of two populations are calculated according to Eqs. (18) and (20).

$$S_1 = \begin{bmatrix}0.0080 & -0.0014 & -0.0010\\ -0.0014 & 0.0026 & 0.0030\\ -0.0010 & 0.0030 & 0.0042\end{bmatrix} \tag{26}$$

$$S_2 = \begin{bmatrix}0.0026 & -0.0004 & -0.0001\\ -0.0004 & 0.0110 & 0.0063\\ -0.0001 & 0.0063 & 0.0072\end{bmatrix} \tag{27}$$

Table 3
Validation results

Number	Actual image status	$f(x_0)$	Class discrimination
1	Defective	−28.0579	Defective
2	Defective	−36.2057	Defective
3	Defective	−61.9810	Defective
4	Defective	−38.1908	Defective
5	Defective	−41.4394	Defective
6	Defective	−30.0435	Defective
7	Defective	−23.8675	Defective
8	Defective	−51.1155	Defective
9	Defective	−40.4942	Defective
10	Defective	−39.4721	Defective
11	Non-defective	34.6429	Non-defective
12	Non-defective	20.8617	Non-defective
13	Non-defective	50.7341	Non-defective
14	Non-defective	6.3967	Non-defective
15	Non-defective	35.0970	Non-defective
16	Non-defective	23.1795	Non-defective
17	Non-defective	7.7370	Non-defective
18	Non-defective	33.0326	Non-defective
19	Non-defective	50.6647	Non-defective
20	Non-defective	29.8239	Non-defective

A pooled covariance matrix is:

$$S_{\mathrm{pooled}} = \frac{1}{2}(S_1 + S_2) = \begin{bmatrix} 0.0053 & -0.0009 & -0.00055 \\ -0.0009 & 0.0068 & 0.00465 \\ -0.00055 & 0.00465 & 0.0057 \end{bmatrix} \tag{28}$$

Then, according to Eq. (23), a multivariate discriminant function to recognize the existence of rust defects is created as follows.

$$f(x_0) = [-79.4754 \quad -8.0797 \quad -84.8142]x_0 + 75.7381 \geq 0 \tag{29}$$

Where, $x_0 = [\mathrm{RMEAN}_0\ \mathrm{GDIFF}_0\ \mathrm{BDIFF}_0]^T$

Therefore, if the value of $f(x_0)$ in a given image is positive, the image is discriminated as non-defective. Otherwise, it is allocated to a defective group.

6. Model testing and validation

In this stage, the developed RUDR method is validated by using new painting images to test the model efficiency. For the validation process, a validation set is created. The set comprises of 20 coating images: 10 as a non-defective group and 10 as a defective group. The conditions of validation images were confirmed by 8 bridge field inspectors in Indiana out of total 14 bridge field inspectors. For the model validation, each validation image was processed to obtain the values of three major variables: RMEAN_0, GDIFF_0, and BDIFF_0. Those three values were input to the multivariate statistical model developed in the previous stage. Then, the value of $f(x_0)$ was calculated to determine the image status. Table 3 shows the calculated discriminant function values of $f(x_0)$ and class discrimination results. The computer for this validation was equipped with a Pentium IV 2.80 GHz CPU and 1.0 GB RAM. The validation results indicate that the discriminant function created for the recognition of rust defects allocates a new observation into a correct class in real time. There are no misclassified images in the validation set. It should be noted that the developed function can classify defective images containing tiny to small rust defects correctly. That means this image processor can be applied for the long-term monitoring of bridge painting conditions. In other words, the existence of rust defects can be continuously checked using this image classifier.

7. Application of rust defect recognition method

This section describes the implementation of the RUDR method in practice to classify given digital images into a correct class. The following stepwise application plan contains three steps, from image acquisition to decision-making on bridge coating conditions.

7.1. Step 1

Image acquisition is the first step for applying the RUDR method. The digitized images obtained through a digital camera are transferred to a computer for image storage. Fig. 9 shows the image acquisition process.

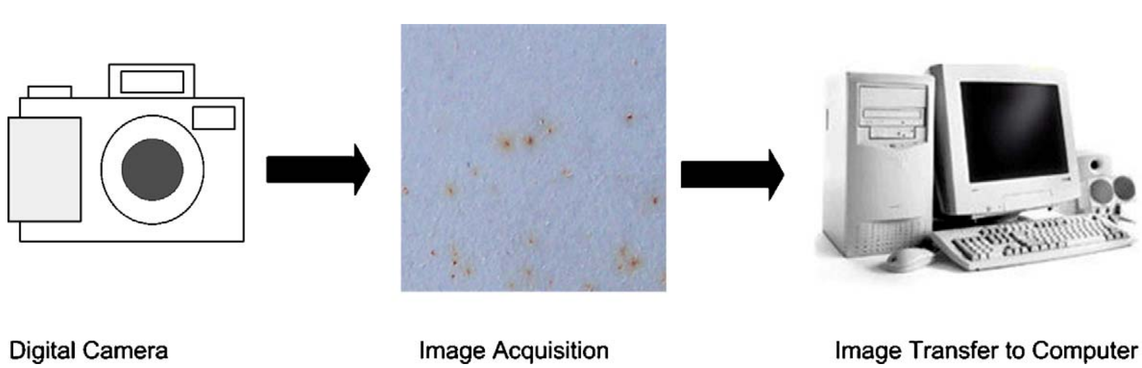

Fig. 9. Image acquisition.

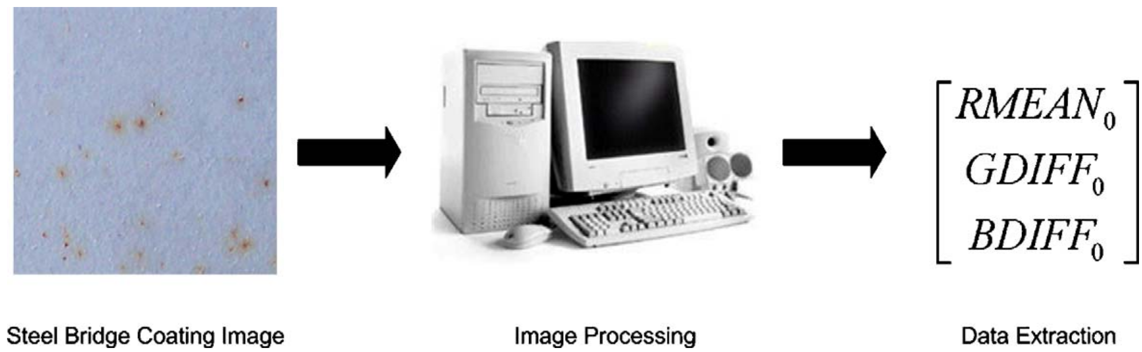

Fig. 10. Data extraction.

7.2. Step 2

The second step is to process the acquired bridge coating images to extract the values of three major variables: $RMEAN_0$, $GDIFF_0$, and $BDIFF_0$. These three variables were determined as the most significant variable in each color channel in the model development process. Fig. 10 shows the data extraction process.

7.3. Step 3

The last step is a decision-making step for allocating the digital images into a correct class: defective or non-defective. The three values are input to the multivariate statistical image processing model. The image classification is made, depending on the calculated values of the image processor. Fig. 11 describes the image classification procedure.

8. Summary and conclusions

This paper presented a novel approach to recognize the existence of bridge coating rust defects by utilizing the digital color space for statistical data acquisition and performing a multivariate statistical analysis.

The rust defect recognition method was realized by following four stages: data acquisition, data analysis, statistical modeling, testing and validation. In the data acquisition stage, bridge painting digital images were prepared to generate two types of data sets: defective and non-defective. The 30 images from each group were used for statistical data generation and multivariate statistical modeling. Then, the images from each group were converted to scatter plots on the RGB color space. From the scatter plots, a number of statistical data or variables were extracted for further processing. In the data analysis stage, the collected variables were analyzed to select significant variables for developing discriminant functions to classify non-defective images into a non-defective group and defective images into a defective class. For the variable test, two types of analyses were performed: the Wilks' lambda analysis and the data range analysis. Based on the analysis results, three variables were determined to have a significant impact to separate two populations. They include: MEAN in red (RMEAN), DIFF in green (GDIFF), and DIFF in blue (BDIFF). The three variables then were used as input variables for multivariate statistical modeling. In the statistical modeling stage, multivariate discriminant functions were created by employing the variables carefully chosen in the previous stage. Finally, in the testing and validation stage, the proposed discriminant model was tested and validated by inputting new observations or digital images into the model. The validation results showed that the discriminant function efficiently allocated all new observations into their correct classes.

The proposed rust defect recognition method can be further developed to realize an automated robotic inspection of bridge coating surface conditions. Bridge condition inspections often appear to be quite dangerous since inspectors have to perform their work under the circumstances where a number of vehicles pass at a high speed. In addition, to acquire coating images from a close distance, extra equipment like a ladder-mounted truck is required to reach high places. Therefore, to resolve these concerns, an inspection robot could be developed and

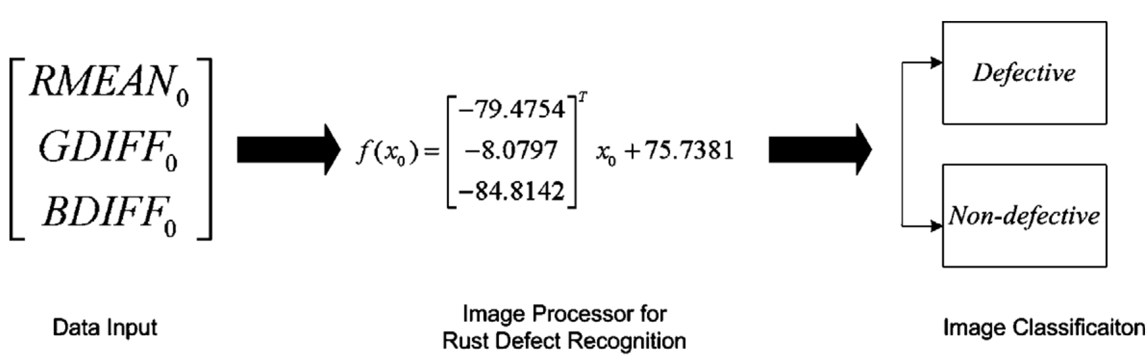

Fig. 11. Image classification.

implemented by transportation infrastructure authorities for practical bridge coating inspections.

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