GRADE CLASSIFICATION OF CORROSION DAMAGE ON THE SURFACE OF WEATHERING STEEL MEMBERS BY DIGITAL IMAGE PROCESSING

P. CHUN[1*], K. FUNATANI[1], S. FURUKAWA[2], and M. OHGA[1]

[1] *Department of Civil and Environmental Engineering, Graduate School of Science and Engineering, Ehime University, Japan*

[2] *West Nippon Expressway Engineering Shikoku Company Limited, Japan*

ABSTRACT

This paper proposes a method to classify the grade of corrosion damage on the surface of weathering steel members by digital image processing. It is reported, by the Public Works Research Institute, the Japan Iron and Steel Federation, and the Japan Bridge Association, that corrosion damage can be classified into five grades by visual examination; however, the classification process is highly subjective and qualitative, so the classification results differ depending on the inspectors. In order to make the inspection process more objective and quantitative, we have developed a method to classify the surface corrosion condition using an image processing technique.

In the proposed method, Otsu's method and texture analysis are employed to classify the corrosion damage. Otsu's method calculates the optimum threshold by separating two classes which minimize the intra-class variance. By using Otsu's method, significant corrosion damage which creates large shadows can be detected. At the same time, texture analysis is employed to evaluate the texture of regions in the image, allowing the detection of minor corrosion damage which cannot be detected by Otsu's method. At the end of the paper, the validity of the proposed method is confirmed using the visual examination results obtained by an inspector. The method is expected to help owners of structures to understand the degree of corrosion damage of weathering steel members, which in turn will help them to develop appropriate maintenance strategies.

Keywords: weathering steel, image processing, corrosion.

1. INTRODUCTION

The deterioration of bridges due to ageing is a serious problem. For example, roughly half the bridges in Japan will be 50 years old or more within 15 years (Fujino & Abe 2002). In order to prevent future catastrophes involving bridges, maintenance, repair, and replacement (MR&R) action is required. However, the effort and cost for MR&R action is not necessarily low.

[*] Corresponding author and presenter: Email: chun.pang-jo.mj@ehime-u.ac.jp

Table 1: Appearance grades based on corrosion characteristics

Appearance grade	Corrosion type	Grain size	Corrosion thickness	Colour tone	Instance of appearance
1	Laminated flaky corrosion	Larger than 25mm	Thicker than 800μm	Vary in colour tone	
2	Imbricate corrosion	5mm to 25mm	400μm to 800μm	Vary in colour tone	
3	Abnormal corrosion of the early phase	1mm to 5mm	Thinner than 400μm	Vary in colour tone	
4	Productive lust layers	Smaller than 1mm	Thinner than 400μm	Dark brown	
5	In the early stage of the formation of productive lust layers	Smaller than 1mm	Thinner than 200μm	Light brown	

Nowadays, weathering steel is widely applied to steel structures, including steel bridges, in anticipation of low maintenance effort and cost (Hara et al. 2007). It is known that weathering steel forms productive rust layers which reduce the corrosion rate, and therefore the maintenance cost is expected to be lower than that of conventional painted steel members. However, it is also known that weathering steel is not necessarily a maintenance-free material (Kihira 2003) in that appropriate maintenance action is required to extend the life of the structure.

In Japan, the Public Works Research Institute, the Japan Iron and Steel Federation, and the Japan Bridge Association published reports on the maintenance of weathering steel which recommended that weathering steel be inspected in its tenth year in order to provide a good prediction of its future condition (the Public Works Research Institute et al. 1992). The reports have suggested that corrosion damage be classified into five grades by visual examination, as shown in Table 1; however, the classification process is highly subjective and qualitative, so the classification results differ depending on the inspectors. In order to make the inspection process more objective and quantitative, we have developed a method to classify the surface corrosion condition using an image processing technique and logistic regression analysis. The analysis results are compared to the visual examination results, and the validity of the proposed technique is satisfactorily confirmed.

2. IMAGE PROCESSING TECHNIQUE

In the conventional inspection process of weathering steel, the inspector manually checks and grades the degree of corrosion, and takes pictures for the record. Table 1, shown in the previous section, contains pictures of all the grades. In this research we conducted image processing and logistic regression analysis using the pictures (the number of pictures = 160) and compared the analytical results to the visual examination results. This section mainly describes the image processing technique employed.

Corrosion damage on the weathering steel has two main visual characteristic, one is the shadow cast by the flaky corrosion and the other is the colour tone variability on the surface. To derive the image feature amounts which evaluate the degree of shadow cast by the flaky corrosion, binarization based on Otsu's method (Otsu 1975) is employed. In addition, texture analysis is conducted to derive the image characteristics which evaluate the colour tone variability.

2.1. Detection of shadow by the binarization method

The pictures used in this research were not taken in a uniform manner. In particular, the effect of flash on the contrast of light and darkness in the pictures is significant. To correct the effect of contrast, equation (1) below is applied to all pixels in the picture.

$$img[i, j] = \frac{img_o[i, j] \times m}{img_m[i, j]} \tag{1}$$

where $[i, j]$ is the position of the pixel, $img[i, j]$ is the pixel value after the correction, $img_o[i, j]$ is original pixel value before the correction, m is the mean pixel value of all pixels in the picture, and $img_m[i, j]$ is the pixel value after applying the mean filter of size $w \times w$ to the original picture. After collection, the pictures are binarized using Otsu's method and the number of shadow parts with an area larger than A is counted. This number is used as one of the image feature amounts in analysing the degree of corrosion by logistic regression analysis. In this research, three different combinations of (w, A) are used; (41, 80), (81, 160), and (161, 320). Examples of the binarization results are shown in Figure 1.

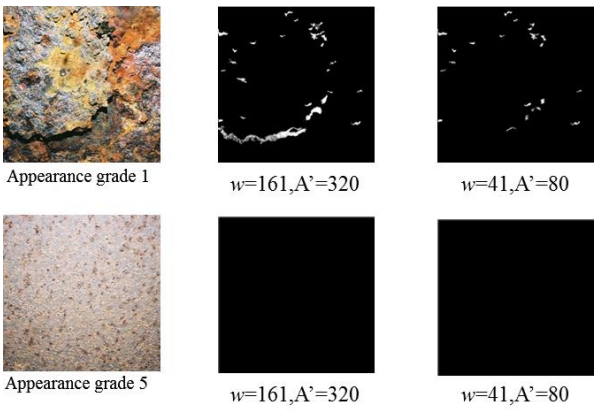
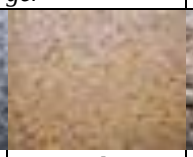


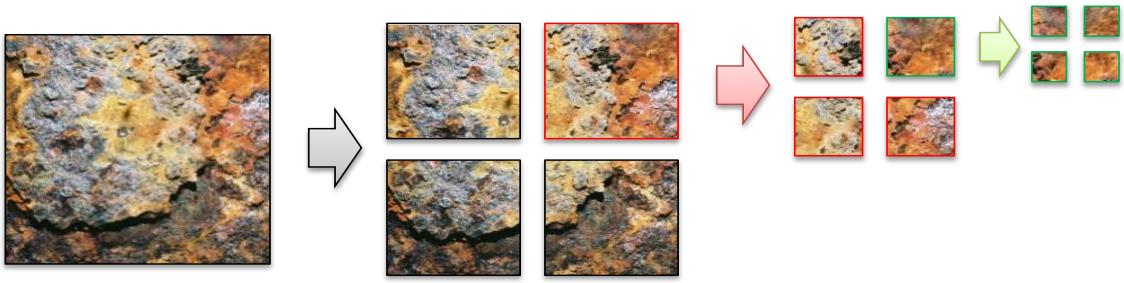
Figure 1: Examples of binarization results of various *w* and *A*

2.2. Texture analysis using co-occurrence matrix

Texture analysis is conducted in this research to evaluate the texture of regions in the pictures, allowing the detection of small areas of corrosion damage which cannot be detected by the binarization method. We have derived four types of texture feature amounts including angular second moment (ASM), contrast (CON), correlation (COR), and entropy (ENT) which are frequently used in texture analysis. Detailed information, including their derivations, can be found in (Tuominen and Pekkarinen 2005). Table 2 shows the relationship between the texture feature amounts and the degree of corrosion damage. In the texture analysis, the distance d between the considered pixels used to develop the co-occurrence matrix has to be determined. This research used d = 7 pixels as a result of trial and error. In addition, we divided the picture into N parts as in Figure 2 to detect and satisfactorily evaluate the corrosion defects of several sizes. N used in this research is 4, 16, and 64.

Table 2: Relationship between texture feature amounts and degree of corrosion

	larger		*smaller*		*Characteristic*
ASM	 Grade 4	 Grade 5	 Grade 3	 Grade 3	The larger the ASM, the higher the uniformity of the picture.
CON	 Grade 2	 Grade 3	 Grade 1	 Grade 5	The larger the CON, the larger the contrast.
COR	 Grade 4	 Grade 5	 Grade 3	 Grade 3	The larger the COR, the stronger the stripe pattern shown.
ENT	 Grade 2	 Grade 3	 Grade 4	 Grade 5	The larger the ENT, the stronger the disorder of the picture.



N = 1 N = 4 N = 16 N=64

Figure 2: Example of image division into N parts

3. LOGISTIC REGRESSION ANALYSIS

Since the outcome of this research is to grade corrosion damage which is a categorical variable, the logistic regression analysis shown in equation (2) was conducted to predict the grade based on the image feature amounts derived in the previous section as predictor variables.

$$y_i = \frac{1}{1+e^{-u}} \qquad (2)$$

$$\text{where} \quad u = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n$$

where y_i is the estimated occurrence probability of grade i, x_n is the image feature amounts, and n is the number of image feature amounts, β_n is the coefficients derived from logistic regression analysis.

To show the validity of this method, k-fold cross validation (McLachlan et al. 2005) was conducted. In the k-fold cross validation, the data is first divided into k equally sized folds. Subsequently k iterations of the validation are performed such that, with each iteration, a different fold of the data is held-out for validation while the remaining k-1 folds are used to derive β_n.

4. RESULTS

Table 3 shows the comparison results of the grade of corrosion damage between the logistic regression analysis results and the visual examination results.

Table 3: Comparison of the results between logistic analysis and visual examination of the grade of corrosion damage

	Results from analysis					
Corrosion grade	1	2	3	4	5	Accuracy rate (%)
1	10	0	0	0	0	100.0
2	2	23	5	0	0	76.7
3	0	4	35	1	0	87.5
4	0	0	2	21	17	52.5
5	0	0	0	9	31	77.5
Total (%)	6.3	14.4	21.9	13.1	19.4	75.0

As in Table 3, the misjudgement between grades 4 and 5 is conspicuous. Specifically, 17 out of every 40 pictures in grade 4 have been misjudged as grade 5 and 9 out of every 40 pictures in grade 5 are misjudged as grade 4. This is because both grades 4 and 5 do not have extensive corrosion damage on the surface; therefore, it is not easy to distinguish them with image processing. However, this misjudgement will not cause serious problems because it is recognized that no MR&R action is required if the damage grade is 4 or 5. Here is an example to explain it. According to The Public Works Research Institute et al. (1992), the future thickness reduction of weathering steel can be predicted using the corrosion grade which is evaluated 9 years after construction. For example, 50 years later, the thickness of weathering steel of grade 4 will be reduced by 0.20mm and that of

grade 5 will be reduced by 0.18mm. Because the difference between them is very small, the resultant stress is not much different. Therefore, it is reasonable to bracket grades 4 and 5 together as grade 4. Table 4 shows the comparison results of the grade of corrosion damage between the logistic regression analysis results and visual examination results after grades 4 and 5 are bracketed. As in Table 4, the developed method using the image processing technique and the logistic regression analysis reproduces the visual examination with an accuracy rate of 91.3%. Furthermore, it is found that analytical results of eight out of every 14 mismatch results seem to be better than the visual inspection results.

Table 4: Comparison results of corrosion grades between logistic analysis and visual examination

Corrosion grade	Results from analysis				Accuracy rate (%)
	1	2	3	4	
1	10	0	0	0	100.0
2	2	23	5	0	76.7
3	0	4	35	1	87.5
4	0	0	2	78	97.5
Total (%)	6.3	14.4	21.9	32.5	91.3

5. CONCLUSIONS

From the comparison results described in the previous section, it is reasonable to conclude that the developed method is sufficiently accurate. In addition, the method removes subjectivity which is seen as a problem in manual visual examination. The method is expected to help owners of structures to understand the degree of corrosion damage of weathering steel members, which in turn will help them to develop appropriate maintenance strategies.

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