Automated Defect Recognition Method by Using Digital Image Processing

Sangwook Lee, Ph.D.
Texas Tech University
Lubbock, Texas

As existing infrastructure systems are aged and deteriorated rapidly, state agencies started searching for more advanced ways to maintain their valuable assets to the acceptable level. One of them is the application of digital image processing. Recently, in the civil engineering domain, digital image processing methods have been developed to the areas of pavement conditions, underground pipeline inspection, and steel bridge coating assessment. The main reasons to count on the advanced technology are due to such advantages as accuracy, objectivity, speed, and consistency. These distinct advantages have brought attention to state agencies to minimize the shortcomings of existing inspection practices. This paper deals with a digital image processing method to apply it to the evaluation of steel bridge coating conditions. Infrastructure condition assessment can be made more accurately and quickly with the aid of computerized processing system. The proposed method in this paper was designed to recognize the existence of bridge coating rust defects. It was developed by making pair-wise comparisons between a defective group and a non-defective group and generating eigenvalues to separate two groups. An automated defect recognition method can make a decision whether a given digitized image contains defects.

Key Words: Bridges, deterioration, image processing, condition assessment

Introduction

As existing infrastructure systems are aged and deteriorated rapidly, state agencies started searching for more advanced ways to maintain their valuable assets to the acceptable level. One of them is the application of digital image processing. Recently, in the civil engineering domain, digital image processing methods have been developed to the areas of pavement conditions, underground pipeline inspection, and steel bridge coating assessment (H. D. Cheng et al. 1999, S. K. Sinha et al. 2003, S. Lee et al. 2005). The main reasons to count on the advanced technology are due to such advantages as accuracy, objectivity, speed, and consistency. These distinct advantages have brought attention to state agencies to minimize the shortcomings of existing inspection practices.

The conditions of steel bridge painting surfaces can be evaluated accurately and quickly by applying digital image processing. Also, machine vision-dependent inspections can provide more consistent inspection results than human visual inspections. Because conventional inspection heavily relies on individual abilities, inspection results are error-prone and may have wide variations between inspectors. The results can be different depending on personal preferences, work experiences, and the workload of the inspectors. It is pretty important to develop reliable infrastructure condition assessment for better maintenance of the assets. In case of bridge coating, bridge managers can more realistically develop long-term cost-effective maintenance programs if they have dependable coating condition data. Also, they can make decisions as to whether a bridge shall be painted again immediately or later. Efficient coating condition assessment is also essential for the successful implementation of steel bridge coating warranty contracting. Under the warranty contracting, an owner and a contractor inspect steel bridge coating conditions on a regular basis and decide whether additional maintenance actions are needed. However, it is extremely difficult to determine if a bridge contains more defects than an allowable level. If they are in conflict, they will go through a lengthy process to reach an agreement.

This paper concerns with rust defects on highway steel bridges. Rust defects are one of the most commonly observed defects on coating surfaces and are to be taken care of appropriately since they can severely affect the structural integrity of bridges and generate unpleasant appearance to passing drivers. A rust defect assessment method needs to be developed to maintain good quality steel bridge painting. For more objective rust defect recognition, digital image recognition methods have been developed for the past few years and they are expected to replace or complement conventional painting inspection methods. This paper proposes a digital image processing method to assess a steel bridge coating surface. The image processing method was developed based on eigenvalues and can be used to recognizing the existence of bridge coating rust defects. An automated defect recognition method can make a decision whether a given digitized image contains defects. The next part shows how much deteriorated infrastructure systems are currently while focusing on bridges, followed by a step-by-step procedure for a system development.

Deteriorated Bridge Infrastructure Conditions

The report cards published by American Society of Civil Engineers (ASCE) are important indicators to understand current conditions of major civil infrastructure systems in this country. A wide range of civil facilities are included for evaluation such as bridges, roads, dams, schools, transit, energy, and so on, and graded on an A to F grading scale (ASCE report card 2009). Lots of leading civil engineers are involved in preparing the report card and the analysis of reports, studies, and other sources are performed. Unfortunately, the overall American infrastructure received a failing grade since the beginning of the studies. The overall grades in 1998, 2001, 2005, and 2009 are D, D+, D, and D, respectively. Also, the report cards indicate the estimated investment needs for the next 5 years to recover infrastructure systems to the acceptable level. The dollar amount needed has been increased. The 2001 ASCE study indicated that the estimated cost for infrastructure renewal was \$1.3 trillion dollars, \$260 billion annually. But, the 2005 study addressed that the renewal cost was \$1.6 trillion, and the 2009 study recorded the highest point, \$2.2 trillion dollars. As existing infrastructure systems are aged rapidly, more and more investment funding becomes necessary to eliminate deficiencies. However, the available funding amount is much less than required and is typically limited. Thus, it is very important to set up an efficient management plan on how to consume limited resources each year. In case of bridges, the GPAs in 1998, 2001, 2005, and 2009 are C-, C, C, and C, respectively (see Figure 1). The points are a little bit higher than the other infrastructure facilities, but still are not satisfactory.

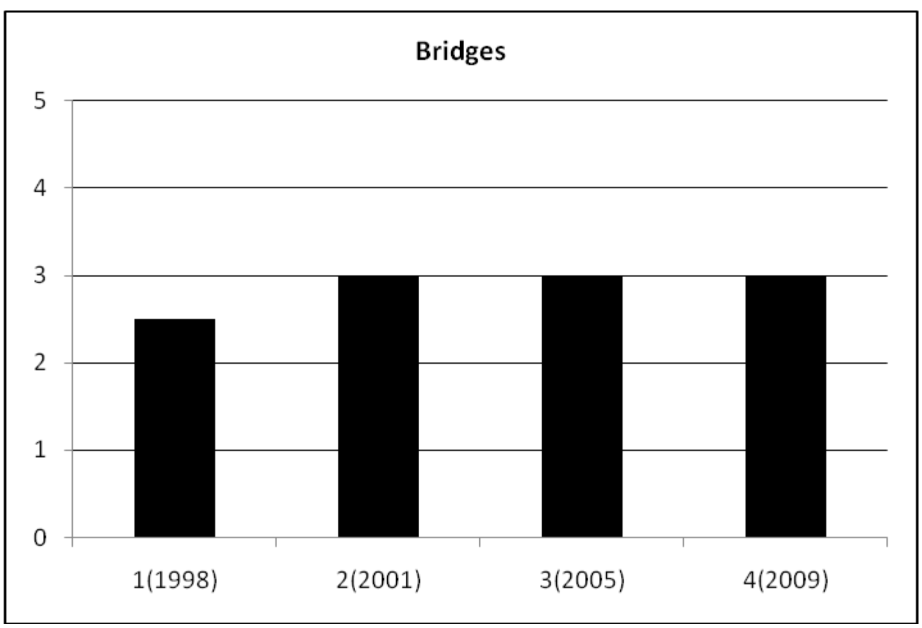

Figure 1: Grade Point Averages of Bridges (<u>Note:</u> 5 is the best, A, and 1 is the worst, F.)

NACE International (2009) proved that the corrosion of metallic structures has made significant impact to every industrial sector in this country. The study to estimate the total economic impact of metallic corrosion in the United States was performed from 1999 to 2001 by CC Technologies Laboratories, Inc. with support from the Federal

Highway Administration (FHWA) and National Association of Corrosion Engineers (NACE). The results of the study showed that the total annual direct cost of corrosion in this country is estimated to be $276 billion that is equivalent to 3.1% of the nation's Gross Domestic Product (GDP). This number did not consider indirect or user costs which are incurred by owners and operators of structures, manufacturers of products, and suppliers of services. Indirect costs include such factor as lost productivity due to outages, delays, failures, and litigation. The study roughly estimated the indirect cost to be equal to the direct cost. Then, the total amount caused from corrosion becomes $552 billion, representing 6% of the GDP. The study divides the U.S. economy into five major sector categories to analyze corrosion direct cost: infrastructure, utilities, transportation, production and manufacturing, and government. The biggest portion comes from utilities that accounted for 34.7% of the total direct cost, and transportation is the second largest category, 21.5%. Infrastructure takes the third place, 16.4%. Under the category of infrastructure, there are four subcategories: highway bridges, hazardous materials storage, gas and liquid transmission pipelines, and waterways and ports. Among these four, highway bridges take the first place and annual direct cost is estimated as $8.3 billion to replace deficient bridges, repair concrete bridge decks and substructures, and maintain bridge painting. The study concluded that corrosion is naturally occurring phenomenon commonly found in the metal-based structures and is continuously developed by the reaction with environment. But, it is controllable and preventable by inventing corrosion-resistive materials and improving corrosion maintenance practices. The study suggested that the U.S. must find ways to implement better corrosion practices and effectively manage existing corroded structures.

Development of Automated Defect Recognition Method

The methodology for the development of a defect recognition method can be classified into three stages: (1) image acquisition, (2) image processing, and (3) data analysis. The detailed description of each stage is given as follows.

Image Acquisition

In the image acquisition stage, steel bridge coating images have to be taken first. Every digital image was acquired by visiting highway steel bridges on the Interstate Highway 65 in Indiana. The color of coating was blue that is 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 feet (0.92 m) from the steel beam surfaces to acquire clear coating images. From the acquired digital images, image data set were prepared for further analysis. Two kinds of testing sets were created: a defective group and a non-defective group. Digital images in the non-defective group contained no rust defects observed. And, images in the defective group enclosed small to medium-level rust defects as shown in the Figure 2.

Figure 2: Bridge Coating Image with Defects *(Image dimensions: 256x256)*

Image Processing

In the image processing stage, original color images are converted to gray-scale images. A color image is consisted of three primary colors: Red, Green, and Blue. A color can be generated by numerical proportion of the three components. Each primary color axis has 256 (2^8) levels of color shade, which means a total of 2^{24} colors can be generated technically from the color space. The origin of the cube corresponds to black and can be designated as (0, 0, 0). The point with (1, 1, 1) indicates white. Three primary colors of red, green, and blue are located on each primary axis. If an image has a combination value of (255, 0, 0), it means pure red. Gray-level images are represented by only 8 bits. A value is assigned to each pixel according to light intensities ranging from 0 to 255. The value of 0 means black and the value of 1 means white. There are lots of sophisticated gray levels between white and black. Therefore, image sizes can be significantly reduced by converting to grayscale images, while improving computing efficiency. Eigenvalues can be obtained by making a pair-wise comparison between digital images, i.e. a defect image and another defect image or a defect image and a non-defect image. The similarity or dissimilarity of eigenvalues from two different group comparisons needs to be examined. A differentiating power will be increased as resulting values show a large difference in the pair-wise comparison. For this process, 15 bridge coating images were prepared for a defect group and the same number of images were prepared for a non-defective group. Thus, total 105 data points can be created from a pair-wise comparison between a non-defective image and another non-defective image. And, total 225 data points can be achieved from a pair-wise comparison between a defect image and a non-defective image.

The procedure to calculate eigenvalues is explained as follows. A digital image can be expressed as a two-dimensional spatial coordinates, *f(x, y)* with the size of $m \times n$. Then, the value of *f* at any point *(x, y)* is proportional to the brightness of the image at that point. Brighter pixels are assigned higher values and darker pixels are assigned lower values. By adding one more reference image, *w(x, y)*, with the same size of *f(x, y)*, the covariance matrix of *Z* (2×2) can be calculated (Strang 1988).

$$Z = \begin{bmatrix} z_{11} & z_{12} \\ z_{21} & z_{22} \end{bmatrix} \qquad (1)$$

Where

$$z_{11} = \left[\frac{1}{m \times n}\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} f^2(x,y)\right] - (\bar{f})^2$$

$$z_{22} = \left[\frac{1}{m \times n}\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} w^2(x,y)\right] - (\bar{w})^2$$

$$z_{12} = z_{21} = \left[\frac{1}{m \times n}\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} f(x,y)\cdot w(x,y)\right] - (\bar{f}\cdot\bar{w})$$

$\bar{f}$ *and* $\bar{w}$ *are the mean gray values of* $f(x,y)$ *and* $w(x,y)$*, respectively.*

There are two eigenvalues obtained from the symmetrical matrix, *Z*. A larger value is denoted as λ_L and a smaller one is denoted as λ_S. The equations to get the values are as follows.

$$\lambda_L = \frac{1}{2}\left[z_{11} + z_{22} + \sqrt{(z_{11} - z_{22})^2 + 4z_{12}^2}\right] \qquad (2)$$

$$\lambda_S = \frac{1}{2}\left[z_{11} + z_{22} - \sqrt{(z_{11} - z_{22})^2 + 4z_{12}^2}\right] \qquad (3)$$

Where $\lambda_L \geq \lambda_S$

The eigenvalues of the matrix Z can be used to extract the shape information about the gray-level distribution in the pair-wise comparison. The larger eigenvalue, λ_L, represents the variance of data along the major-axis of the distribution shape, and the smaller eigenvalue, λ_S, represents the variance of data along the minor-axis of the shape in the two-dimensional distribution map. For example, Figure 3 shows the result of mapping gray-level distribution of an image (Figure 2) to the image itself. A 45^o-diagonal line is obtained in the resulting gray-level distribution map. Each pixel values are placed along the positive diagonal direction. In this case, a larger eigenvalue shows the variance of the diagonal (or major) direction. But, this curve does not have a variance in the orthogonal direction, with a small eigenvalue a zero, since two identical images are compared.

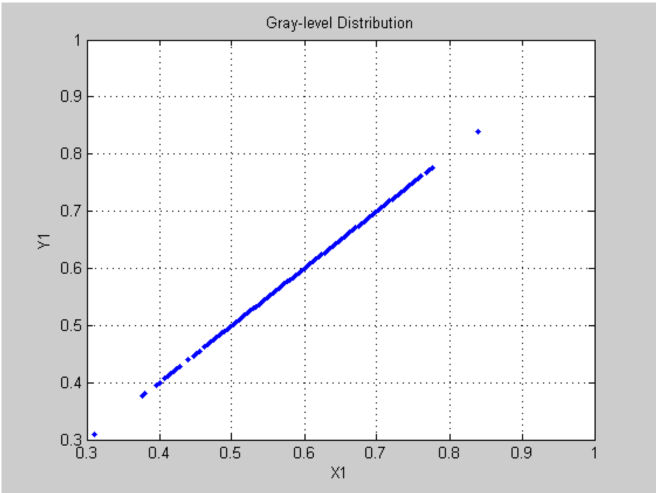

Figure 3: Gray-level Distribution for Two Images

Data Analysis & Results

In this stage, bridge coating images are processed to generate eigenvalues. Two kinds of pair-wise comparisons were performed: two non-defective images and a non-defective image and a defective image. Total 105 data points were obtained from the comparison of two non-defective images (Group A). Also, total 225 data points were achieved from the comparison of a non-defective image and a defective image (Group B). Figure 4 shows the gray-level distribution of Group A and Table 1 presents descriptive statistics based on the figure. Five values (minimum, maximum, average, standard deviation, and variance) were calculated to a small eigenvalue and a large eigenvalue.

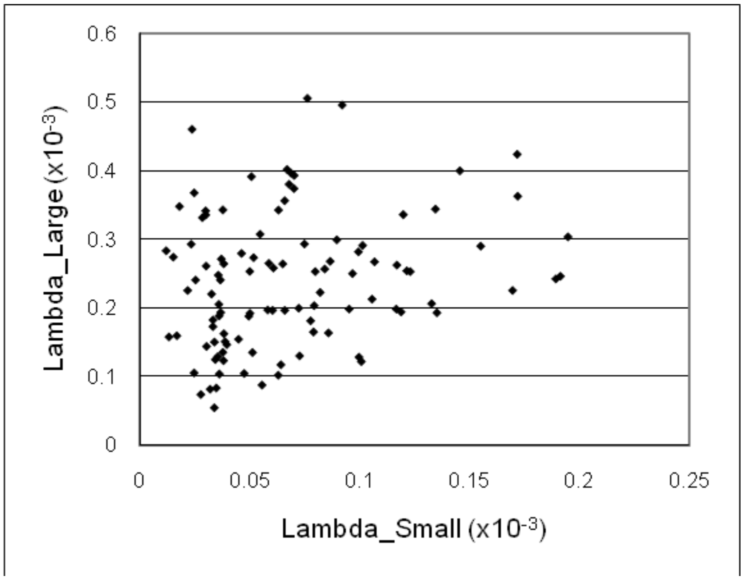

Figure 4: Eigenvalue Distribution of Group A

Table 1: Resulting Statistics of Eigenvalues in Group A

λ	Minimum	Maximum	Average	Stdev	Variance
λ_S	0.0121	0.1948	0.0686	0.0432	0.0019
λ_L	0.0546	0.5063	0.2395	0.0972	0.0094
Note: Stdev is a standard deviation.					

Figure 5 shows the gray-level distribution of Group B and Table 2 presents descriptive statistics of five values based on the figure.

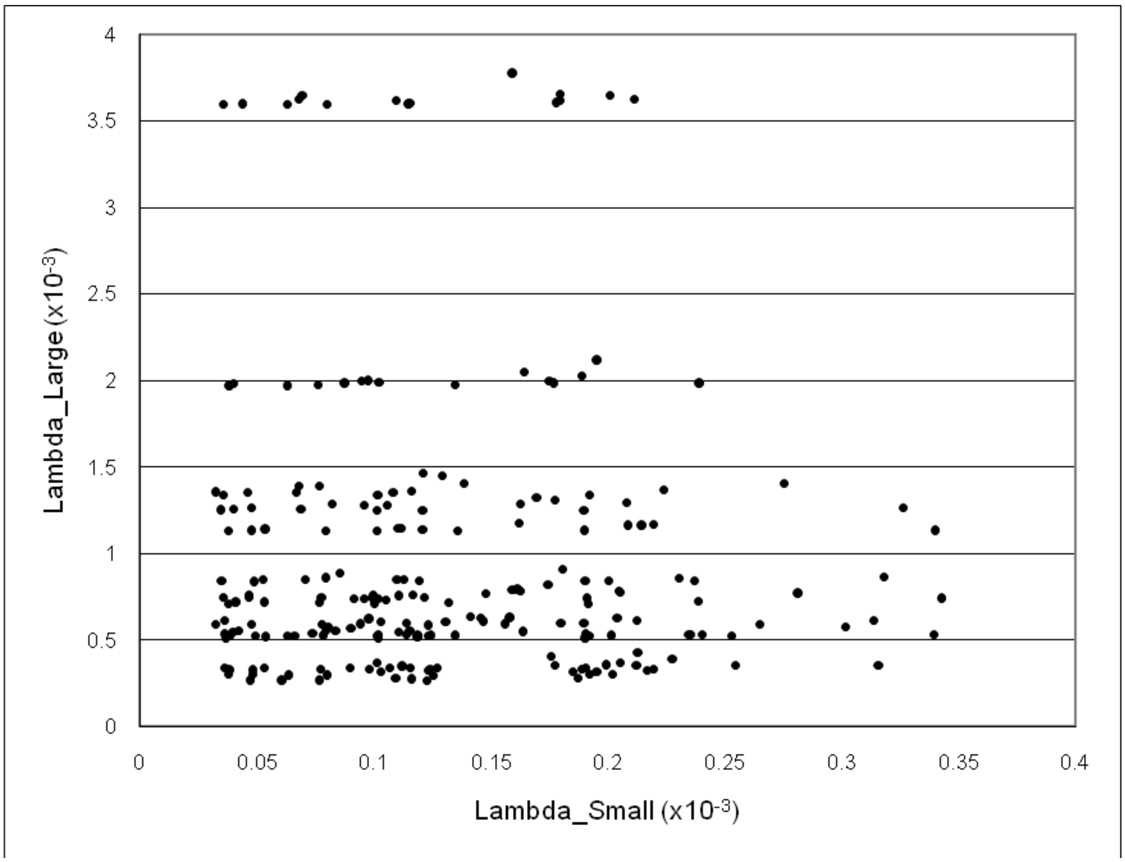

Figure 5: Eigenvalue Distribution of Group B

Table 2: Resulting Statistics of Eigenvalues in Group B

λ	Minimum	Maximum	Average	Stdev	Variance
λ_S	0.0322	0.3428	0.1308	0.0719	0.0052
λ_L	0.2667	3.7773	1.0005	0.8360	0.6989
Note: Stdev is a standard deviation.					

Discussions

Data results from image processing and resulting two-dimensional distribution maps present the following important findings.

(1) The distribution patterns from Figure 4 and Figure 5 need to be compared each other. Figure 4 illustrates that most data points close each other and are strongly clustered together within a small region when processing two different non-defective images. However, data points become scattered widely in vertical and horizontal axes, and are dispersed on a large area when processing a non-defective image and a defective image at the same time. The degree of spread becomes greater when it comes to a large eigenvalue, rather than a smaller one.

(2) To identify the range of data points, a minimum and a maximum values were acquired from both groups. Small eigenvalues range from 0.0121 to 0.1948, and large eigenvalues range from 0.0546 to 0.5063 in Group A. In Group B, small eigenvalues range from 0.0322 to 0.3428, and large eigenvalues range from 0.2667 to 3.7773, while showing much wider distribution in both eigenvalues.

(3) Resulting statistics reveal that large eigenvalues are superior to small eigenvalues to detect bridge coating defects in a gray-scale image processing. This feature can be explained by comparing data ranges of large and small eigenvalues. Also, it can be demonstrated by looking at average values in both groups. The average values of small eigenvalues are 0.0686 and 0.1308 in Group A and B, respectively. However, the average values of large eigenvalues are 0.2395 and 1.0005 in each group, while showing wider difference between two groups.

(4) In summary, experimental results demonstrated that it seems effective to distinguish defective images from non-defective images by developing an eigenvalue-based defect recognition method. Two groups, Group A and Group B, showed different distribution patterns and dissimilar data ranges, while some data points were overlapped in the two groups. A large eigenvalue λ_L has a greater differentiation capability than a small eigenvalue λ_S from the experimental analysis. Most large eigenvalues were distributed below 0.4 in a Group A. On the other hand, the eigenvalues were placed more than 0.5 in a Group B.

Conclusions and Limitations

This paper presented a novel approach to recognize the existence of bridge coating rust defects by utilizing a digital image processing to better assess a bridge coating surface. The image defect recognition method was developed by making pair-wise comparisons and calculating eigenvalues which were chosen as a key feature to distinguish defective images from non-defective images.

The rust defect recognition method was realized by taking the following three stages: image acquisition, image processing, and data analysis. In the image acquisition stage, bridge painting digital images were acquired and prepared to generate two types of data sets: defective and non-defective. In the image processing stage, a pair-wise comparison was performed to generate eigenvalues. The first comparison was performed between two different non-defective images where total 105 data points were generated. And, the next comparison was carried out between a defect image and a non-defective image where total 225 data points were generated. Large and small eigenvalues were generated and distributed on a two-dimensional distribution map. Also, five statistical values were calculated and presented in tables. The results from this experimental study were summarized in details in the above discussion section. Experimental results demonstrated that an eigenvalue-based defect recognition method is effective to distinguish defective images from non-defective images.

Some limitations this research work identified need to be addressed. Digital image processing is an effective tool to assess external conditions of a facility. However, there is a limitation to examine internal conditions. In case internal conditions of a structure are in question, additional technology should be considered. Also, this research work was performed to propose a generic methodology to detect bridge coating defects and present testing results. In order to put this technique into practice, more comprehensive field testing is required. It would be better to work with DOT personnel to obtain a right to access more steel bridges and take more field images. By doing this, the validity of this methodology can be enhanced.

References

Cheng, H. D., Chen, J., Glazier, C., and Hu, Y. G. (1999). Novel approach to pavement cracking detection based on fuzzy set theory. *Journal of Computing in Civil Engineering*, 13(4) 270-280.

Sinha, S. K., Fieguth, P. W., and Polak, M. A. (2003). Computer vision techniques for automatic structural assessment of underground pipes. *Computer-Aided Civil and Infrastructure Engineering*, 18(2) 95-112.

Lee, S., Chang, L. M., and Chen, P. H. (2005). Performance comparison of bridge coating defect recognition methods. *Corrosion*, NACE International, 61(1), 12-20.

ASCE Report Card. (2009, September 14). *Report card for america's infrastructure* [WWW document]. URL http://www.infrastructurereportcard.org

NACE International. (2009, September 14). *Corrosion costs and preventive strategies in the United States* [WWW document]. URL http://events.nace.org/publicaffairs/images_cocorr/ccsupp.pdf

Strang, G. (1988). *Linear Algebra and Its Applications,* Harcourt Brace Jovanovich, Orlando, Florida.