

Color Image-based Defect Detection Method and Steel Bridge Coating

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This paper presents a highly efficient method for recognizing the existence of bridge coating rust defects using color image processing. The detection of defects on steel bridge surfaces during the maintenance and diagnosis of bridge structures is important to ensure the safety and reliability of these structures. More advanced techniques such as digital image processing are studied more and developed as existing infrastructure systems are aged and deteriorated rapidly. Recently, image-based defect recognition and assessment methods have attracted considerable attention in the civil engineering domain due to their accuracy, speed, and lower cost. The proposed method in this paper is a decision-making system based on color image processing. It was developed by processing original bridge coating images to generate RGB (red, green, and blue) values and calculating eigenvalues from each digitized image. The values from two different groups, a defective group and a non-defective group, are compared each other to understand the feasibility of this approach. Finally, an automated defect recognition method is presented and tested with more images. This method can be used to make a decision whether a given digitized image contains defects.
Key Words: Bridges, color images, condition assessment, decision-making

Introduction

Digital image processing has been applied to diverse industry disciplines. Recently, image-based defect recognition and assessment methods have attracted considerable attention in the civil engineering domain ([1], [2], [3], and [4]). The wide application of digital image processing can be attributed to the following advantages: accuracy, objectivity, speed, and consistency. These distinct advantages will facilitate existing inspection methods to be replaced or supplemented by advanced inspection methods. It is really important to know current conditions of bridge structures by inspecting highway bridges on a regular basis. Federal Highway Administration (FHWA) required that all highway bridges be inspected at least once every two years by qualified inspectors. The inspection results are recorded in the National Bridge Inventory (NBI). According to the information in the NBI, around 27% of the national bridges were either structurally deficient or functionally obsolete in 2002. This status may be worsened over time since more bridge structures are aged and deteriorated and will experience increasing traffic. Even if keeping correct bridge conditions is extremely important to manage and administer a maintenance program, there are several limitations to be addressed. According to Chase and Ghasemi (2009), the NBI database is one of the most comprehensive sources of inventory of bridge conditions, but is not suitable for bridge performance measurement or the development of bridge maintenance programs. This is mainly due to the lack of knowledge of bridge performance especially in the level of components, rather than a system. Another limitation of the database includes the lack of information on the condition of specific elements such as protective systems, as well as the absence of information on local damage or deterioration. These limitations have made developing better bridge management systems difficult. In addition, conventional inspection results tend to be subjective and affected by inspector experiences, personal opinions, or the workload of inspectors. Thus, it may be more important to develop machine-vision dependent inspections to identify bridge deteriorations or damages since they can provide more consistent inspection results. Maryland Department of Transportation (MDOT) also indicated that a current inspection program cannot guarantee that every problem will be detected and recommended to use high-tech equipment to detect flaws in the bridges and tunnels not easily detected by current practices [6].

Efficient rust defect recognition methods may also contribute to the successful implementation of steel bridge coating warranty contracting where the owner, usually state agencies, and the contractor inspect bridge coating conditions on a regular basis and decide whether additional maintenance actions are needed. According to Russell, J. S. et al. (1999), a warranty is a guarantee of the integrity of a product and of the contractor's responsibility to repair or correct any deficiencies for several years after a project is completed. State agencies are able to shift postconstruction performance risk to the contractor who then has more freedom to choose the materials and construction methods for the product. So, the concept of warranty is relatively new and pretty different from the traditional design/bid/build contracting system where a contractor is not responsible for the long-term performance of highway or bridge projects. Warranty contracts are applied to various end products or services such as asphalt and rubberized asphalt pavement, bridge painting, bridge components, concrete pavement patches, intelligent transportation system components, landscaping and irrigation systems, pavement marking, etc. Among these, bridge painting projects have been warranted most mainly because the Michigan Department of Transportation has required warranties on all bridge painting projects since 1996. Indiana Department of Transportation has tentatively set up the maximum warranty period of five years and the maximum allowable rust percentage of 0.3% within a total steel structure. If the painting rust defect percentages on bridge surfaces are estimated at less than or equal to 0.3% with a five-year period, the work will be accepted. However, it is extremely difficult to determine if the rust percentage is above or below 0.3% with naked eyes.

This paper addresses the recognition of 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 highway users. Lee (2010) addressed a rust defect recognition method previously by processing gray-scale images to generate image data. But, this paper presents a method by directly processing color images without converting images to gray-scale images. The feasibility of the color image processing in this regard will be studied through this paper. There is no definite answer for which approach is more effective. There is no perfect method developed in this regard so far. There are pros and cons in each image processing method. For example, the gray-scale image processing tends to simplify a processing procedure, which often results in computation efficiency. In contrast, the color image processing usually requires more processing steps and processing time. Thus, a study to make a comparison between two different approaches is necessary. The next parts show the step-by-step procedure to develop a digital image processing method to assess a steel bridge coating surface.

Development of Defect Recognition Method

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

Image Acquisition and Preparation

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. Bridge coating images were taken at a distance of around 3 feet (0.92 m) with a consumer digital camera. A digital camera is widespread these days and can be purchased at a pretty cheap price. The color of coating was blue, one of the most commonly used painting colors. Indiana currently applies a three coat system for its steel bridges since 1999. After a surface preparation by using a commercial sand blast cleaning, coating consists of a dry film 75 μm (3 mil) thick inorganic zinc primer coat, followed by a dry film 100 μm (4 mil) thick epoxy intermediate coat and a 75 μm (3 mil) thick polyurethane finish coat. All acquired images were transferred to computer storage for further processing and analysis. Figure 1 shows a schematic diagram from image acquisition to storage. 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.

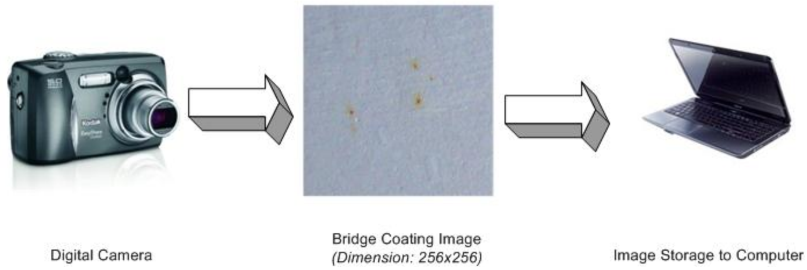

Figure 1: Coating Image Acquisition (Image dimensions: 256x256)

Image Processing

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. Likewise, every color is represented on a 3-dimensional space and this color space is called the RGB color space shown in Figure 2 where three primary colors of red, green, and blue are located on each primary axis. If an image has a combination value of (1, 0, 0), it means pure red. On the other hand, a gray-level image only has a one-dimensional representation. A value is assigned to each pixel according to light intensities ranging from 0 to 255. A number of sophisticated gray levels are placed between white and black.

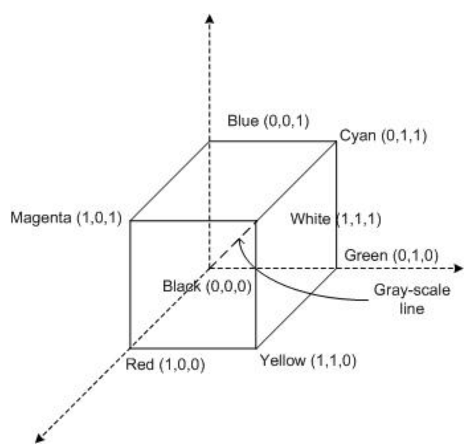

Figure 2: RGB Color Space

To induce eigenvalues, three primary color information (i.e. red, green, and blue) has to be first calculated from a digital image. Then, a covariance matrix of ***C*** (*3X3*) can be calculated from the matrix set of the three colors. After achieving the covariance matrix, eigenvalues can be calculated as follows (Strang 1988). There are two image testing sets prepared for this process, a defective group and a non-defective group. Each group contains 30 bridge coating images, the size of which was *256x256* pixels.

$$\boldsymbol{Cx = \lambda x \ or \ (C - \lambda I)x = 0} \qquad (1)$$

In the above equation, the number of λ is called an eigenvalue of the matrix ***C***, and the vector ***x*** is the associated eigenvector. To find the eigenvalues, determinant of ***(C - λI)*** has to be calculated first. This determinant is a polynomial of degree *n*. So, *n* eigenvalues exist.

Data Analysis & Results

In this stage, each digital bridge coating image is processed to generate eigenvalues. There are two digital image groups: a defective group and a non-defective group. Three eigenvalues from each image processing can be obtained and are called a small eigenvalue (λ_S), a medium eigenvalue (λ_M), a large eigenvalue (λ_L). Figure 4 shows the eigenvalue distributions of defective images and Table 1 presents descriptive statistics based on the figure. Five statistic values (minimum, maximum, average, standard deviation, and variance) were calculated to a small, a medium, and a large eigenvalue curves.

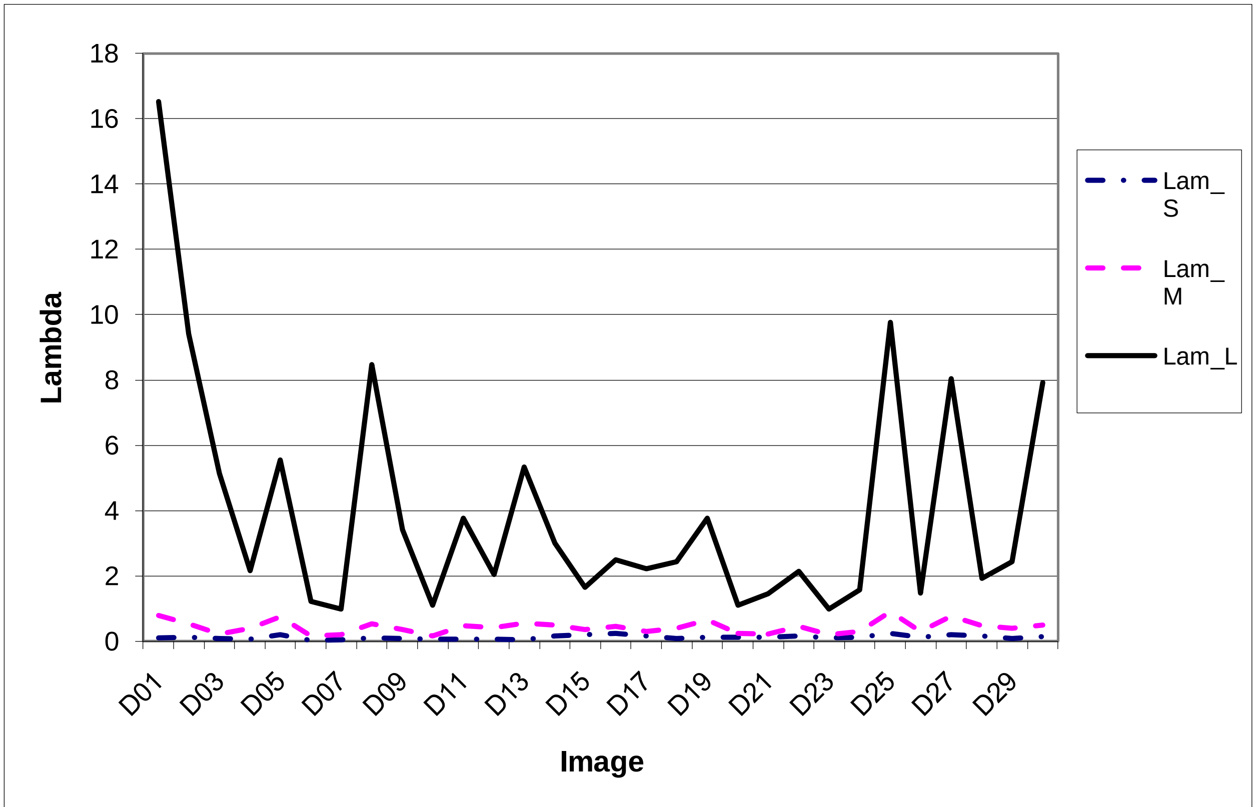

Figure 4: Eigenvalue Distribution of Defective Images

Table 1: Resulting Statistics of Defective Images

λ	Minimum	Maximum	Average	Std	Variance
λ_S	0.0232	0.2472	0.1201	0.0564	0.0032
λ_M	0.1532	0.9014	0.4310	0.1943	0.0378
λ_L	0.9760	16.5314	3.9839	3.5731	12.7672
Note: Std is a standard deviation.					

Figure 5 shows the eigenvalue distributions of non-defective images and Table 2 presents descriptive statistics of five values based on the figure.

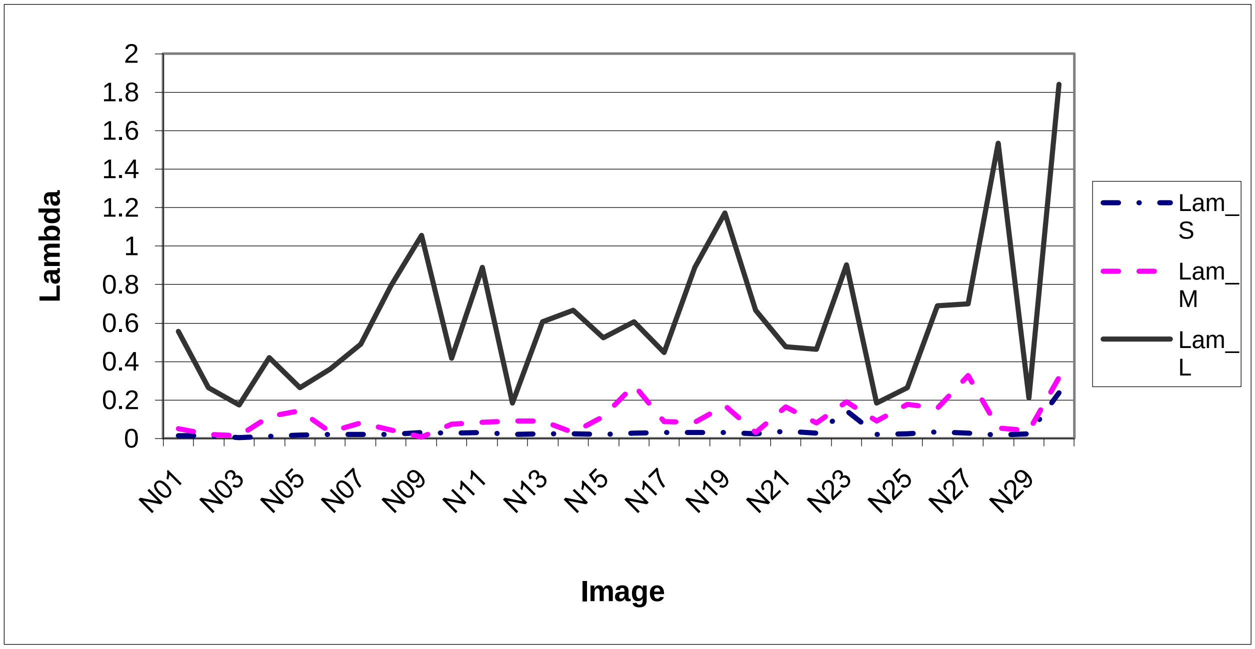

Figure 5: Eigenvalue Distribution of Non-defective Images

Table 2: Resulting Statistics of Non-defective Images

λ	Minimum	Maximum	Average	Std	Variance
λ_S	0.0051	0.2372	0.0345	0.0448	0.0020
λ_M	0.0078	0.3258	0.1086	0.0843	0.0071
λ_L	0.1735	1.8406	0.6239	0.3927	0.1542
Note: Std is a standard deviation.					

Discussions

Data results from image processing and resulting eigenvalue distribution maps present the following important findings.

(1) The distribution patterns from Figures 4 and 5 need to be examined. Data distribution of small eigenvalues (λ_S) are pretty stable and do not show much fluctuation in both groups, defective images and non-defective images. This fluctuation gets larger when it comes to medium eigenvalues (λ_M). And, the degree of data spread becomes greatest when it comes to large eigenvalues (λ_L). This was a similar pattern observed from both groups.

(2) A minimum and a maximum values were obtained from both groups to identify the range of data points. In a defective group, λ_S ranged from 0.0232 to 0.2472, λ_M ranged from 0.1532 to 0.9014, and λ_L ranged from 0.9760 to 16.5314. In a non-defective group, λ_S ranged from 0.0051 to 0.2372, λ_M ranged from 0.0078 to 0.3258, and λ_L ranged from 0.1735 to 1.8406. In overall, data distributions of defective images are much wider than those of non-defective images.

(3) The average values of defective images are 0.1201, 0.4310, and 3.9839, respectively. And, the average values of non-defective images are 0.0345, 0.1086, and 0.6239, respectively. As the eigenvalues become greater, the difference between two groups is also increased significantly.

(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 image groups showed different distribution patterns and dissimilar data ranges, while some data points were overlapped

in the two groups. Large eigenvalues have a greater differentiation capability than medium or small eigenvalues from the experimental analysis.

Testing and Validation

In this stage, the developed color image-based defect recognition method is tested and validated by using more coating images to test the model efficiency. The number of images for this process was 10 coating images among which five images were defective and five images were non-defective. Each testing image was processed to generate three eigenvalues, λ_S, λ_M, and λ_L. Then, these values are compared with group average eigenvalues listed in Tables 1 and 2. Average eigenvalues from defective images were (λ_S, λ_M, λ_L) = (0.1201, 0.4310, 3.9839). And, average eigenvalues from non-defective images were (λ_S, λ_M, λ_L) = (0.0345, 0.1086, 0.6239). A given image will be assigned to a defective or a non-defective group based on the Euclidean distance. The distance between points ***p*** and ***q*** can be defined as follows.

$$D(\boldsymbol{p},\boldsymbol{q}) = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2} \qquad (2)$$

Where, $\boldsymbol{p} = (p_1, p_2, \ldots, p_n)$ and $\boldsymbol{q} = (q_1, q_2, \ldots, q_n)$ in a n-dimensional space

If the distance of a tested image is closer to the average point of a defective group, the image will be classified as defective. Otherwise, the image will be classified as non-defective. Table 3 shows the testing results. These testing results indicate that an eigenvalue-based defect recognition method is pretty functional and effective. The overall recognition accuracy rate was quite high, 90%.

Table 3: Model Testing Results

Group		Predicted		Accuracy (%)
		Non-defective	Defective	
Actual	Non-defective	5	0	100
	Defective	1	4	80

Conclusions and Limitations

This paper presented the recognition of rust defects on highway steel bridges. Rust defects are one of the most commonly observed defects on coating surfaces. A defect recognition method was developed by processing color coating images directly without converting to gray-scale images.

The rust defect recognition method was developed by taking the following three stages: image acquisition and preparation, image processing, and data analysis and results. In the first 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, bridge coating images in each group were processed to generate color information, i.e. red, green, and blue. Then, three eigenvalues, i.e. small, medium, and large, were generated to make a comparison between two groups. Finally, eigenvalue distributions of a defective group and a non-defective group were generated and presented on a two-dimensional distribution map. Also, five statistical values were calculated and presented in a table form. A validation process demonstrated that a color-image based defect recognition method is effective to distinguish defective images from non-defective images.

There are some limitations associated with this research work. Digital image processing is an effective tool to assess surface conditions of a facility. However, there is a limitation to examine internal conditions. In case the internal conditions of a structure are in question, additional technology should be sought. Also, this research work was performed to propose a generic methodology to detect bridge coating defects and present testing results. However, more comprehensive field testing is required in order to put this technique into practice. It would be desirable to work with DOT personnel to obtain a right to access more steel bridges and take more sample images.

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