STEEL BRIDGE CORROSION DETECTION BY WAVELET TRANSFORM THEORY

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ABSTRACT

Corrosion causes section loss in steel members and hence can be responsible for disastrous consequences, particularly if it affects critical components. However, the subjective nature of inspection methods is a contentious issue in infrastructure management and has been identified as a critical obstacle to producing effective rating assessment. As a result, providing objective, accurate and reliable information has become a very important issue for the effective management and rehabilitation of bridges. The main purpose of this research is to explore the application of wavelet transforms to analyze steel corrosion images and provide objective and accurate information on the level of corrosion present. This paper illustrates that the time and frequency domain can be used to process images to identify and measure the status of the surface coating on steel bridges. The preliminary results of this research show that the proposed approach appears to be feasible. The approach provides an opportunity to evaluate corrosion based on objective and consistent analytical information.

KEY WORDS

Bridge inspection, Steel Bridge, Corrosion, Wavelet Transform, Image Processing

INTRODUCTION

The Federal Highway Administration estimates that about 40% of the 600,000 highway bridges in the United States are rated deficient (Dunker and Rabbat 1995). The deterioration of anticorrosion coatings exposes steel and hence plays an important role in the structural deficiency rating of a bridge. However, little attention has been placed on specifically determining precise appraisal ratings, especially in the area of coating quality assessment, a crucial element of steel bridge quality assurance (Hunt et al. 1997). Current inspection techniques rely on human visual inspection (Shubinsky 1994). Therefore, they are subjective and time-consuming. The subjective nature of inspection methods is a contentious issue in

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infrastructure management and has been identified as a critical obstacle to effective rating assessment (Hunt et al. 1997, Chang and Abdelrazig 1999, and Abdelrazig and Chang 2000). As a result, providing objective, accurate and reliable information has become a very important issue for the effective management and rehabilitation of bridges.

The main purposes of the research introduced in this paper are to explore the application of wavelet transforms to analyze steel corrosion images and to provide objective and accurate information on the level of corrosion. This paper demonstrates that by using a wavelet transform approach, we can decompose an image of the surface of a steel bridge to discover features about that image. Hence, the time and frequency domain can be used to process images to identify and measure the status of the surface coating on steel bridges.

CAUSES OF STEEL CORROSION AND INSPECTION STANDARDS

"The most recognizable type of steel deterioration is corrosion. Bridge inspectors should be familiar with corrosion since it can lead to a substantial reduction in member capacity" (Bridge Inspector's Reference Manual 2002). Corrosion causes section loss in steel members and hence can be responsible for disastrous consequences, particularly if it affects critical components. It is most commonly caused by cycles of exposure of steel to wet and dry conditions. Also, the chemicals that are used for different operations such as de-icing, may act as catalysts and hence the effect of moisture is accelerated. Some of the common types of corrosion include: Environmental corrosion, Stray current corrosion, Bacteriological corrosion, Stress corrosion, and Fretting corrosion.

Currently in U.S., most coating inspection procedures are based on the standards from American Society for Testing and Materials (ASTM) and The Society for Protective Coatings (SSPC) (Abdelrazig and Chang 2000). The standard related to corrosion inspection is listed in Table 1. ASTM uses rating from 0 to 10 and suggests the area needed to be repainted according to the related rating (SSPC 1989). The corrosion performance rating is listed in Table 2. The procedure heavily relies on human vision to estimate the percentage of corrosion to two decimal places. A slight difference between the corrosion percentage estimates may result in different corrosion ratings and affect the area to be repainted. On one hand, unnecessary repainting due to the overestimation of corrosion percentage will increase the repair expenses. On the other hand, underestimation of corrosion percentage might increase the probability of corrosion expansion and section loss. As a result, a consistent and quantitative procedure is needed to assess the extent of corrosion.

Table 1 SSPC inspection standard (SSPC 1989)

		Corrosion occurred area	Surface status
Degree	0	$A<0.1\%$	Almost no corrosion
	1	$0.1\% \leq A<1.0\%$	Slight corrosion
	2	$1.0\% \leq A<5.0\%$	Obvious corrosion
	3	$A \geq 5.0\%$	Entirely corroded

Table 2 ASTM corrosion performance rating (SSPC 1989)

Corrosion Rating	Assessment Description	Areas to be Repainted (%)
10	No rust or less than 0.01% rust	0
9	Less than 0.03% rust	0
8	Few isolated spots,less than 0.1% rust	0
7	Less than 0.3% rust	0
6	Extensive rust spots,less than 1% rust	8
5	Less than 3% rust	18
4	Less than 10% rust	40
3	Approximately 1/6 of surface rusted	60
2	Approximately 1/3 of surface rusted	100
1	Approximately 1/2 of surface rusted	100
0	Approximately 100% of surface rusted	100

WAVELET TRANSFORM (WT)

Image processing is usually applied in domains where it is hard to extract information from the original domain function. By using WT to do image processing, we can easily decompose an image of the surface of a steel bridge to discover more information and specific characteristics about that image. By comparing the characteristics of the image and inspection standards, we can automate the inspection procedure and determine an objective rating of the corrosion present on that bridge surface.

The concepts on which WT is based have existed for decades. However, the beginnings of the WT as a specialized field can be traced back to the mid-1980s where the WT approach was developed to interrogate seismic signals (Grossmann and Morlet 1984). The WT approach was developed based on Fourier Transform (FT) to overcome the shortcomings in FT. A WT uses an alternative approach called multi-resolution analysis (MRA) (Mallat 1989, 1998) to analyze a signal at different frequencies with different resolutions. MRA is designed to give good time resolution and poor frequency resolution at high frequencies, and good frequency resolution and poor time resolution at low frequencies. There are many different types of wavelet transforms. Among those types of wavelet transform, Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) are two types of wavelet transform. Each are described below:

1) Continuous Wavelet Transform (CWT)

The CWT was developed to overcome the Short-Time Fourier Transform (STFT) resolution problem (Grossmann and Morlet 1984). The concept is similar to STFT where the signal is divided into different segments. However, there are two main differences between the STFT and the CWT (Polikar 1995):

- The Fourier transforms of the windowed signals are not taken.
- The width of the window is not fixed.

$$CWT(a,\tau) = \frac{1}{\sqrt{a}} \int f(t)\psi\left(\frac{t-\tau}{a}\right)dt \qquad a,\tau \in R; a \neq 0 \quad \text{..........} \quad (1)$$

In the above equation (Grossmann and Morlet 1984), the $\psi(t)$ term, called basic or mother wavelet, is used to generate the other window functions.

2) Discrete Wavelet Transform (DWT)

The first DWT was developed by Alfréd Haar, a Hungarian mathematician, in 1909 (Polikar, 1999). If (a, τ) in eq. (1) are discrete wavelets, let $a = a_0^m, \tau = n\tau_0 a_0^m$, m and n are integers.

$$DWT(m,n) = \int f(t)\psi_{mn}(t)dt \quad \ldots\ldots (2)$$

Where $\psi_{mn}(t) = a_0^{-\frac{m}{2}}\psi(a_0^{-m}t - n\tau_0) \quad , \quad \psi_{00} = \psi(t)$ …… (3)

And for an orthonormal wavelet $\int \psi_{mn}(t)\psi_{m'n'}(t)dt = \begin{cases} 1 & m = m', n = n' \\ 0 & others \end{cases}$ …… (4)

2D MULTI-RESOLUTION ANALYSIS

In 1989, Mallat (1989) proposed the Multi-Resolution Analysis (MRA) concept to decompose a signal into several segments with different frequencies. For a two dimensional (2D) signal, the signal is decomposed into four segments (Figure 1): low frequency (ca), horizontal high frequency (chd), vertical high frequency (cvd), and diagnostic high frequency (cdd). Then the low frequency part is again decomposed into 4 segments. The procedure is repeated until the desired level of decomposition is achieved. The ca segment contains the main energy of the original signal. The chd part contains the horizontal lines of the original signal. The cvd part contains the vertical lines of the original signal. The cdd part contains the intersection-section points of the horizontal and vertical lines of the original signal.

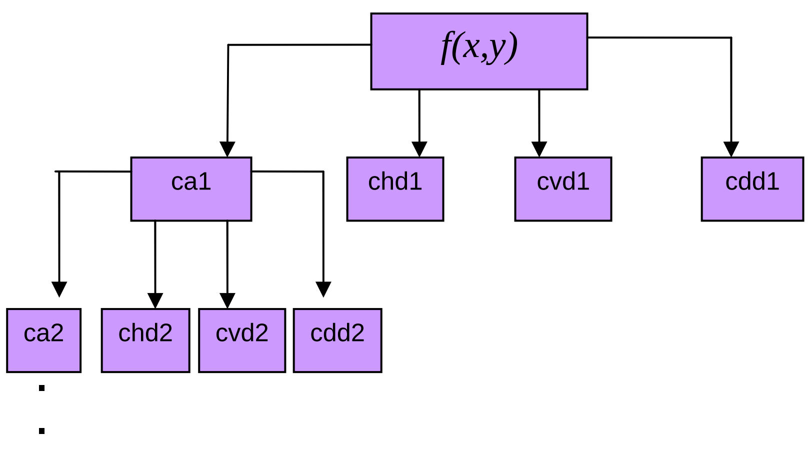

Figure 1 Two dimension signal decomposing

IMAGE PROCESSING RELATED RESEARCH

Recently, researchers have used different kinds of computerized methods to automatically evaluate the quality of bridges coating by analyzing images. Chen et al. (2002) used Multi-resolution Pattern Classification to assess steel bridge coatings with gray scale images. Chang and Abdelrazig (1999, 2000) used a neural network to assess facility surfaces. These research projects successfully illustrate image recognition and analysis capabilities of neural networks. Thanks to the progress of computer technology, image processing has become practical and cost-efficient, and we are now able to analyze complicated images with image processing. Antonini et al. (1992) proposed a scheme for image compression that takes into account features both in the space and frequency domains.

METHODOLOGY

The current inspection approach relies on human vision which is subjective and time-consuming. Slightly misclassifying the corrosion area would result in very different maintenance decisions. This paper present a research project that employed wavelet transforms to analyze images of bridge steel girder surfaces and attempted to provide objective, accurate information about the extent of corrosion on that surface for inspectors to use to make decisions. In this section, the RGB model and analysis procedure used to analyze these images shall be explained.

THE RGB MODEL

There are a lot of different models that can be used to represent an image. Based on the observation from the test images in the research, the corrosion parts in the images tend to have significantly different colors from the coating color. Moreover, severely corroded areas tend to have a darker color. Therefore, in this research, the RGB model is adopted to represent the image. The RGB model can be represented as a 3D coordinate system (Figure 2). The three axes of this model are red, green, and blue, respectively. The minimum and maximum values for each axis are from 0 to 255. For example, white is (255, 255, 255) and yellow is (255, 255, 0). If the value above the maximum value (i.e. 255) or below the minimum value (i.e. 0), the color cannot be shown in the model. By setting different vectors within the space, most of the colors can be represented in the RGB model.

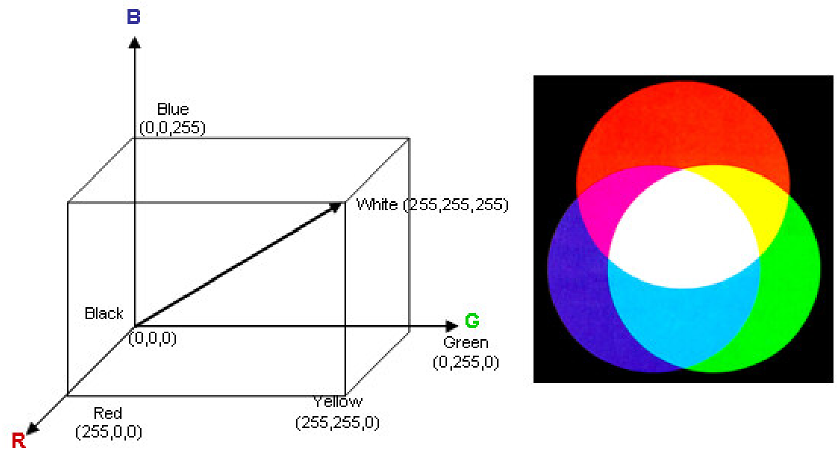

Figure 2 The RGB model

Image Analysis Algorithm

Figure 3 shows the image analysis algorithm:

1) The image is preprocessed (e.g. contrast is enhanced) if needed.
2) The standard deviations (S.D.) of the RED, GREEN, and BLUE colors are calculated to see which color component has the maximum S.D. The one which has the maximum S.D. value has the biggest difference between painting and corrosion and is chosen as the basis for the analysis.
3) The image is analyzed with a WT, decomposing the image, modifying the coefficients.
4) To distinguish between corrosion and coating, the coating color will be multiplied by a scale factor to let the coating color exceed the maximum visible color (i.e. 255). Therefore, those color values below 255 shall comprise the corroded areas. If the image can not be decomposed properly, users can go back and adjust the scale factor. By using 255 as a threshold, the initial percentage of corrosion for the entire image can be calculate as follows:

$$InitialPercentageofCorrosion = \frac{numbers \quad of \quad color \quad value < 255}{Total \quad numbers \quad of \quad entire \quad image} \times 100\% \quad .. (5)$$

5) The corrosion image is extracted and further decomposed to four different levels of color to get more detailed information. Different levels of colors represent the severity levels of corrosion.
6) Weights may be added to adjust the corrosion percentages and hence the severity level. For example, the darkest color of a corroded part represents the most serious corrosion. All areas represented by that color should be considered as severely corroded. Thus, the weight for that color is 1.0. Based on the experiments in this research, the weights for the four corrosion levels were established from serious to minor, (i.e. the color from dark to light) are set to be 1.0, 0.7, 0.3, and 0.1, respectively.
7) Finally, the system uses the result and the SSPC, ASTM standards to help inspectors making maintenance decisions.

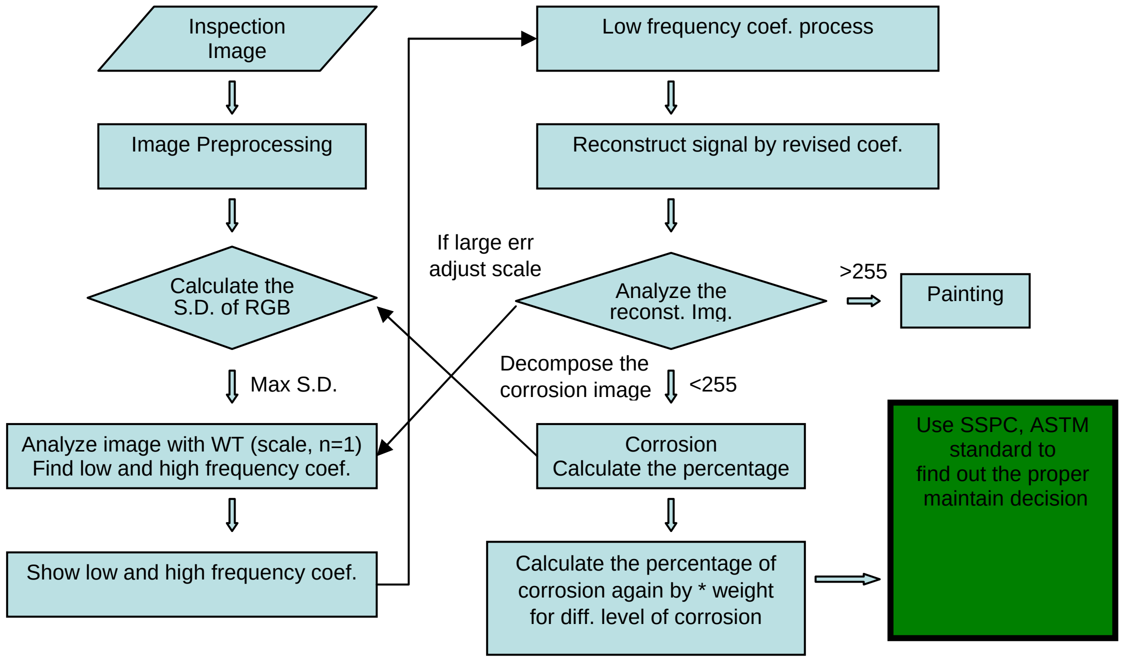

Figure 3 The Image Analysis Algorithm

CASE STUDY

For an actual case study for the effectiveness of this approach, the three test images shown in Table 3 were used. Test case 1 will be described in detail. The approximate corrosion percentage is the percentage of corrosion pixels divided by total image pixels. It was determined manually using Adobe Photoshop. Pixels in the image that looks like corrosion were selected. Thus, there are some estimate errors. The reason of determining the approximate corrosion percentage is to give a rough comparison basis for the research approach. Based on the corrosion percentage, the rating for SSPC and ASTM can also be determined.

1) Test case 1 is a 640x480 pixel steel image with yellow coating color. The corrosion percentage is approximately 3.83%, the SSPC level is 2, and the ASTM rating is 4.

2) Test case 2 is a 640x480 pixel steel image with blue coating color. The corrosion percentage is approximately 3.85%, the SSPC level is 2, and the ASTM rating is 4.

3) Test case 3 is a 1024x768 pixel steel image with blue coating color. The corrosion percentage is approximately 16.79%, the SSPC level is 3, and the ASTM rating is 2.

TEST CASE 1

The results are described as follows:

1) The S.D. of the GREEN color in the image was the maximum S.D among the three colors RED, GREEN and BLUE. Therefore, the GREEN color image was used to further analyze the extent of corrosion.

2) The percentage of each corrosion level was multiplied by different weights to reflect different levels of corrosion. The weights in this study are based on the rule that assigned larger values to more serious corrosion. The weights for four corrosion levels, from serious to minor, are set to be 1.0, 0.7, 0.3, and 0.1, respectively. From Figure 4, the system extracted most of the corrosion-affected region. The corrosion-area percentage before multiplying the weight was 6.82%. Figure 4 also shows the portion (Aratio) of each corrosion level of the corrosion image. The final corrosion percentage after applying the weight was 4.05 %. The error rate compared to the approximate corrosion percentage (3.83%) is approximately 5.6%.
3) Finally, the results were compared to the SSPC and ASTM standards to help inspectors making maintenance decisions. From the SSPC standard, it is level 2 corrosion (i.e., obvious corrosion). The suggestion from ASTM for maintenance is to clean the corrosion and repaint 40% of the surface. The system determined the correct rating for both standards.

OTHER CASES

1) Test case 2: The final corrosion percentage after applying the weight was 3.86 %. The error rate compared to the approximate corrosion percentage (3.85%) is approximately 0.13%.
2) Test case 3: The final corrosion percentage after applying the weight was 19.70 %. The error rate compared to the approximate corrosion percentage is approximately 17.35%. The approximate corrosion percentage has more estimation error in this test case due to the complexity of the image. Therefore, the percentage comparison does not really help to justify the performance of the system. Although the error rate is relatively larger than that of other two test cases, from the extracted corrosion image in Table 3, the system extract most of the corrosion part in the image.

The error rate and extracted corrosion image for three test cases are listed in Table 3.

CONCLUSIONS

The research presented in this paper applied WT to analyze images of corrosion to provide objective, accurate, and reliable information for inspectors concerning the extent of that corrosion. In test case 3, it is hard to justify the system performance based on the error rate due to the complexity of the corrosion image. However, the extracted corrosion image showed that most of the corrosion part was extracted by the system. The error rate is still within an acceptable range to allow system to predict a reasonable rating. The preliminary results of this research show that the proposed approach appears to be feasible. The approach provides an opportunity to evaluate corrosion based on objective and consistent analytical information. The approach has also shown that by adopting expert or prior knowledge to adjust weights for different levels of severity of corrosion, accuracy may improve. Hence, this WT-based approach can be further improved with the aid of expert opinion to ascertain better estimates.

Table 3 Three test case studies

Name	Test case 1	Test case 2	Test case 3
Original Image			
Size	640x480 pixels	640x480 pixels	1024x768 pixels
Approx. Corrosion % (Manually classified)	3.83% (11779 /307200 pixels)	3.85% (11842 /307200 pixels)	16.79% (132016 / 786432 pixels)
SSPC	2	2	3
ASTM Area	40 %	40 %	100 %
Extracted Corrosion Image			
Cal. Corrosion %	4.05 %	3.86 %	19.70 %
Error rate	5.63%	0.13%	17.35%

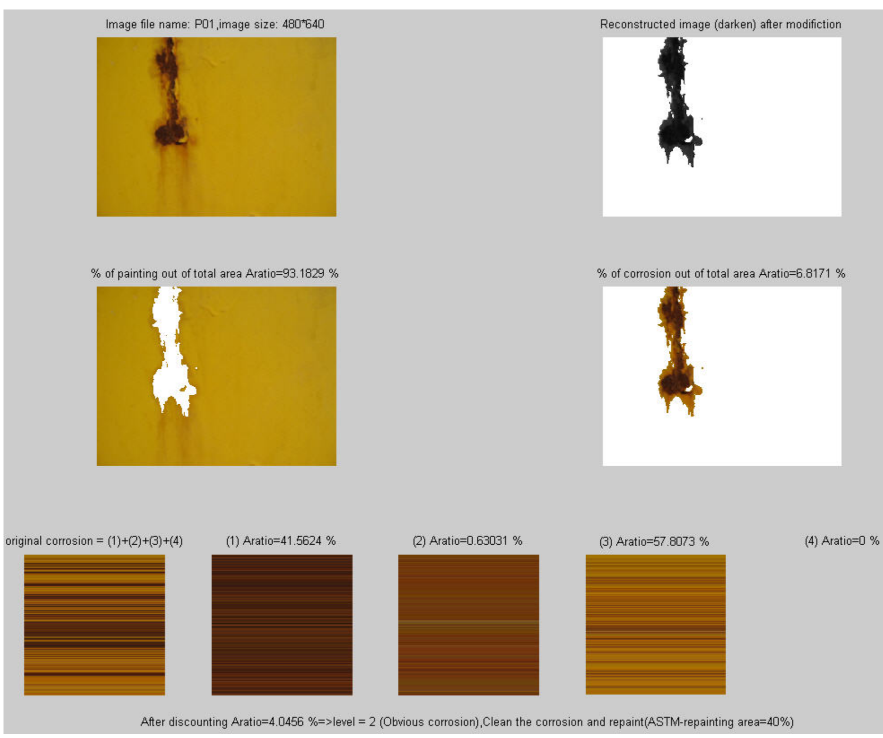

Figure 4 Test case 1 analyzed results

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