Computerized Bridge Coating Defects Assessment Using Neuro-Fuzzy Thresholding Method

by

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ABSTRACT: Digital image processing has been prevalently adopted in different areas. In the construction field, image processing has been used for defect detection on steel bridge painting and underground sewer systems. However, non-uniformly illuminated images always cause recognition problems and affect the accuracy. In order to resolve these problems, the neuro-fuzzy recognition approach (NFRA) was proposed. The NFRA segments an image into three areas based on illumination and conducts area-based thresholding. The neural network is used in this approach for automatic generation of three threshold values, with the three average illumination values of the three areas as the input. The fuzzy adjustment is utilized to smooth and adjust the gray level values of the image pixels along the boundaries. In this paper, the framework of NFRA and the rationale of the fuzzy adjustment will be presented, followed by the comparison of the recognition results using NFRA and the multi-resolution pattern classification (MPC) method. The result shows that the proposed NFRA performs fairly well on recognizing rust images. Finally, the conclusions will be drawn.

KEYWORDS: Fuzzy Adjustment; Multi-Resolution Pattern Classification (MPC); Neural Networks; Neuro-Fuzzy Recognition Approach (NFRA)

1. INTRODUCTION

As computerized technologies were widely utilized, digital image processing was also prevalently adopted in many industries (Abraham et al. 1997; Croall and Mason 1992; AbdelRazig et al. 1999; Chen and Chang 2000). In the construction area, image processing has been used for defect recognition on steel bridge painting and underground sewer systems.

There are a number of advantages when using computerized digital image processing. Computerized digital image processing is able to distinguish millions of shades of colors, which are hard to be distinguished by human eyes, and enables the analysis and comparison of images. In addition, digital image processing can accurately calculate defect percentages. Even though digital image processing has such powerful capabilities, there are still some drawbacks that need to be resolved, especially when image quality is poor. Non-uniform illumination is the most frequent problem that accompanies a poor-quality image. In order to obtain better and reasonable results while conducting digital image processing, methods that can diminish the bad effects from non-uniform illumination are needed.

Intelligent surface coating assessment uses neuro-fuzzy recognition approach (NFRA) to resolve the recognition problems resulting from non-uniform illumination. Because the colors in steel bridge rust images are simple, all rust images are converted to grayscale before further processing without losing much information (Chang 2000). The conversion of color images to grayscale images reasonably simplifies the complexity and expedites the recognition process. Then, the illumination-based image segmentation is conducted. In this segmentation, each of the grayscale images is segmented into

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three areas in accordance with the illumination values of the pixels in the image. The average illumination values of the three areas are calculated afterwards and sent to a pre-trained neural network to obtain three corresponding threshold values, which will be used for illumination-based image thresholding later. In the mean time, a fuzzy adjustment is utilized to smooth the threshold values of the pixels along the boundaries between different areas. Finally, image thresholding is applied based on the obtained threshold values to get a binary image containing only the object pixels and the background pixels (Chen 2001).

In order to test the feasibility of the proposed NFRA, the recognition results using NFRA and the multi-resolution pattern classification (MPC) method were compared (Chen 2001).

2. FUZZY ADJUSTMENT

The fuzzy adjustment is to be applied to the image pixels on both sides of the boundaries between areas. Figure 1 illustrates the schematic representation of the fuzzy adjustment. Two inputs are included in this fuzzy system, the "positive difference" and the "negative difference." The output is the "gray level adjustment." A set of nine If-Then rules constitutes the kernel of the fuzzy system, as indicated in Table 1 (Chen 2001).

Both the inputs "positive difference" and "negative difference" have three levels: large, medium, and little. The universe of discourse (the range of input) for both inputs ranges from 0 to 20. Differences (both positive and negative) larger than 20 are counted as 20.

The "gray level adjustment" is the output of the fuzzy system. It is a value ranging from –0.1 to 0.1 and contains five different levels: negatively large, negatively a little, still, positively a little, and positively large. The adjusted gray level value can be expressed by the following equation:

$$G_{new}(x,y) = G_{old}(x,y) * (1 + \beta) \quad (1)$$

where $G_{new}(x,y)$ and $G_{old}(x,y)$ represent the new gray level value and the old gray level value of the pixel located on (x,y), respectively. β is the gray level adjustment amount, which is the output of the fuzzy adjustment system.

3. NEURO-FUZZY RECOGNITION APPROACH (NFRA)

The neuro-fuzzy recognition approach (NFRA) conducts an area-based image recognition process. Figure 2 illustrates the flow of NFRA, which contains seven steps (Chen 2001).

Step 1 – Step 2:
Image acquisition is the first step of NFRA. Image data can be acquired using a digital camera and transferred to a computer. The second step is to convert the image to gray scale using image processing software. In order to process in an efficient way, an image is usually converted to gray scale before processing.

Step 3:
After converting the image to gray scale, the illumination value of each pixel can be found. All the pixels in the image are separated into three groups in accordance with their illumination values. Illumination values are between 0 and 1, with 0 the darkest and 1 the brightest. The average illumination values of the three areas will be computed and serve as the input to a pre-trained neural network. Figure 3 illustrates the illumination-based image segmentation.

Step 4:
Once the image segmentation is completed, the three average illumination values of the three areas will be sent to a pre-trained neural network to generate three corresponding threshold values, which range from 0 to 255. The training set for the neural network should be diverse so that the trained neural network would be fault-tolerant. Figure 4 illustrates the neural computing process of the three threshold values.

Step 5:
In this step, the fuzzy adjustment is utilized to adjust the gray level values of the image pixels along the boundaries. The gray level adjustment range is from –10% to +10%. Figure 5 shows the flow of fuzzy adjustment.

Step 6:
In this step, each area is thresholded according to its corresponding threshold value. Pixels with gray level values smaller than the threshold values (i.e., darker) are considered as defects (or rusts in this case), and pixels with gray level values larger than the threshold values (i.e., brighter) are considered as background. Figure 6 depicts the illumination-based thresholding process. In Figure 6, the values in the grayscale image represent the gray level values of pixels. The thresholded image is a binary image, with 0's representing the background and 1's representing the defects (rusts).

Step 7:
When the thresholding of all the three areas is completed, the defects in the image can be recognized and the defect percentage can be calculated by counting the percentage of the defect pixels out of all the pixels in the image. Figure 7 illustrates the defect recognition and calculation.

4. MULTI-RESOLUTION PATTERN CLASSIFICATION (MPC) METHOD

There are two resolution levels involved in the multi-resolution pattern classification (MPC) method: the fine resolution level and the coarse resolution level. The fine resolution level (sometimes called the measurement level) refers to the original image. The coarse resolution level refers to a high-dimensional feature space that is mapped from the fine resolution level (Chang 2000). MPC can be broken down into the following steps:

1. At the fine resolution level, the original image is divided into a number of small image blocks. The number of image blocks affects the resolution of the classified (or clustered) image. The larger the number of image blocks, the better the resolution of the classified image.

2. After the division of an image at the fine resolution level, the features of each image block will be extracted and serve as the basis for image classification. In MPC, the spatial gray level dependence method (SGLDM) and the gray level difference method (GLDM) will be adopted for feature extraction (Chang 2000).

3. When feature extraction for each image block is complete, each image block will be mapped onto a high-dimensional feature space as a vector (which can also be thought of as a point in the high-dimensional feature space), with the number of features equal to the dimension of the vector. All the feature vectors in the high-dimensional feature space form the coarse resolution level. The number of vectors (or points) in the coarse resolution level equals the number of image blocks in the fine resolution level.

4. A clustering algorithm will be applied to the coarse resolution level to classify the feature vectors in the high-dimensional feature space. The nearest mean reclassification (NMR) algorithm will be used for feature vectors clustering in MPC (Fukunaga 1990).

5. When the classification of feature vectors is finished, the classification result will be mapped back to the fine resolution level to further cluster the original image. Feature vectors of the same group in the coarse resolution level will make their corresponding image blocks in the fine resolution level fall in the same group.

Figure 8 illustrates the flow of MPC. The structure of the MPC can be represented by the "multi-resolution pyramid" as shown in Figure 9, where *n* features were extracted from each image block (Chen 2001; Chang 2000).

5. COMPARISON OF NFRA AND MPC

In this section, NFRA, an artificial intelligence method, was compared with MPC, a statistical method proven to be effective in recognizing rust images (Chang 2000). In Figures 10 and 11, it can be seen that both methods performed effectively on rust images. In Figure 10, NFRA seemed to have better performance, because some rust spots in the upper left corner were not recognized by MPC. In Figure 11, both methods had similar recognition results. From the viewpoint of processing time, MPC, which took 4.5 minutes to process an image, is faster than NFRA, which took 5 minutes to process one. Through comparison to MPC, the performance and effectiveness of NFRA can be proven and justified.

6. CONCLUSIONS

In the construction industry, digital image processing has been experimented for use in defect recognition of steel bridge painting. However, there are still some problems associated with this newly proposed application. Poor quality images remarkably affect the accuracy of this application, and non-uniform illumination is usually the cause.

In order to resolve the problem, an illumination-based image recognition technique combining a neural network and a fuzzy adjustment is proposed. The neuro-fuzzy recognition approach (NFRA) segments an image into three parts in accordance with the illumination of the pixels in the image and thresholds an image based on the three areas. The intelligent learning ability of the neural network is utilized for automatic generation of three threshold values through input of the three average illumination values from the three segmented areas. The fuzzy adjustment is used for smoothing the gray level values of the image pixels along the boundaries.

From the application of NFRA to steel bridge rust images, it can be seen that NFRA works effectively on rust image recognition. Through comparing NFRA to the multi-resolution pattern classification (MPC) method, it was proven that NFRA is an effective approach for rust image recognition. The advantage of NFRA is its fault-tolerance characteristic. The disadvantage of NFRA is the system has to be trained before being used.

In brief, the proposed NFRA provides a new approach utilizing artificial intelligence for image recognition that may lead to automation of steel bridge coating assessment in the near future.

7. REFERENCES

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Table 1. If-Then Rules for Fuzzy Adjustment

IF	Positive Difference	AND	Negative Difference	THEN	Gray Level Adjustment
IF	*Large*	*AND*	*Large*	*THEN*	*Still*
	Large		*Medium*		*Positively Small*
	Large		*Small*		*Positively Large*
	Medium		*Large*		*Negatively Small*
	Medium		*Medium*		*Still*
	Medium		*Small*		*Positively Small*
	Small		*Large*		*Negatively Large*
	Small		*Medium*		*Negatively Small*
	Small		*Small*		*Still*

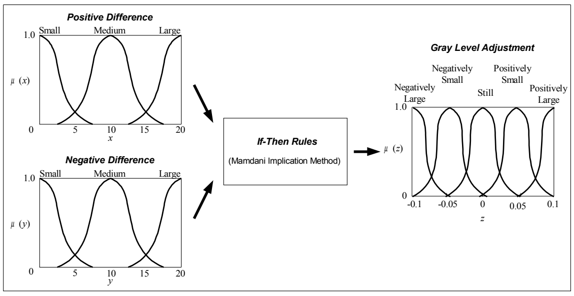

Figure 1. Schematic Representation of Fuzzy Adjustment

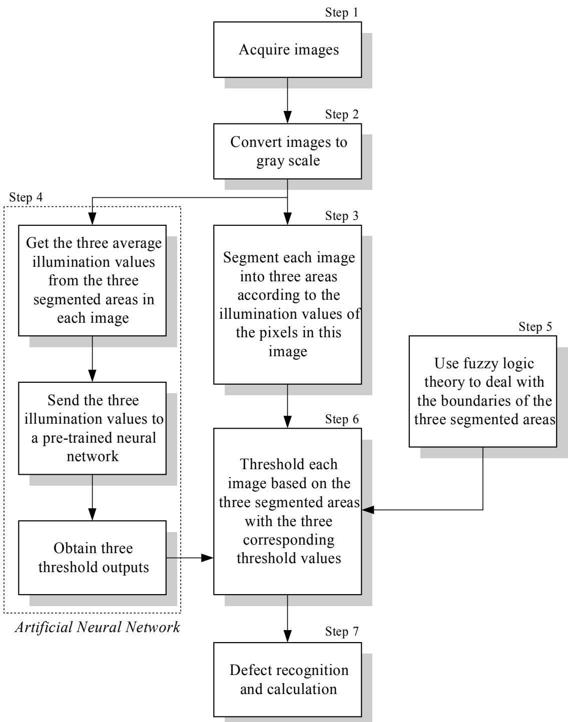

Figure 2. Neuro-Fuzzy Recognition Approach (NFRA)

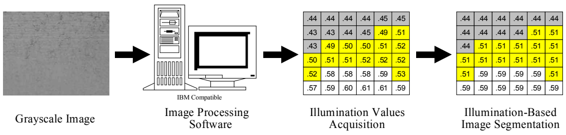

Figure 3. Illumination-Based Image Segmentation

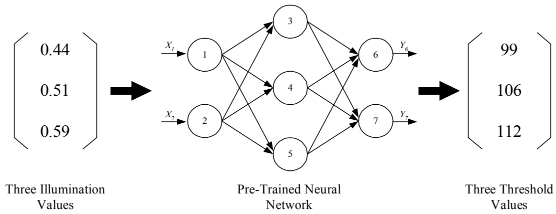

Figure 4. Neural Computing of Threshold Values

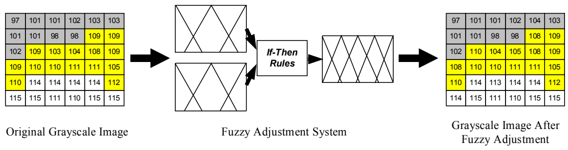

Figure 5. Fuzzy Adjustment on Boundary Pixels

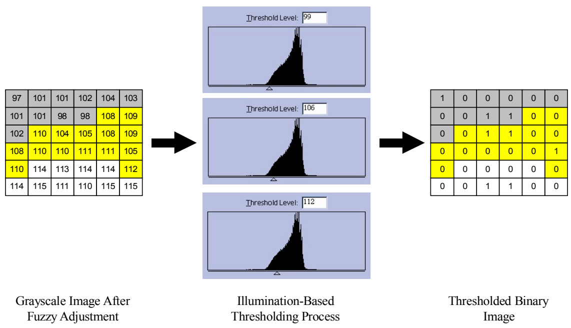

Figure 6. Illumination-Based Thresholding Process

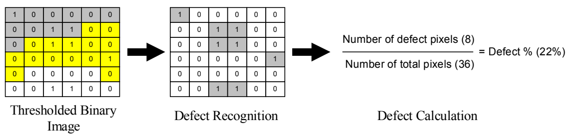

Figure 7. Defect Recognition and Calculation

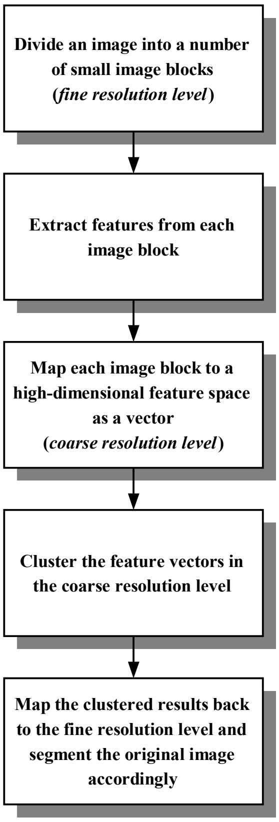

Figure 8. Flow of Multi-Resolution Pattern Classification (MPC) Method

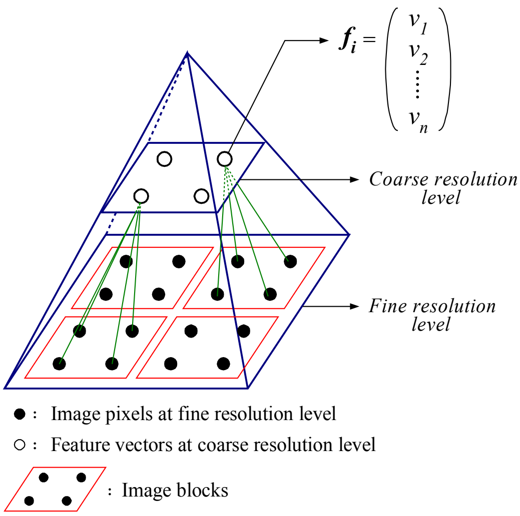

Figure 9. Multi-Resolution Pyramid

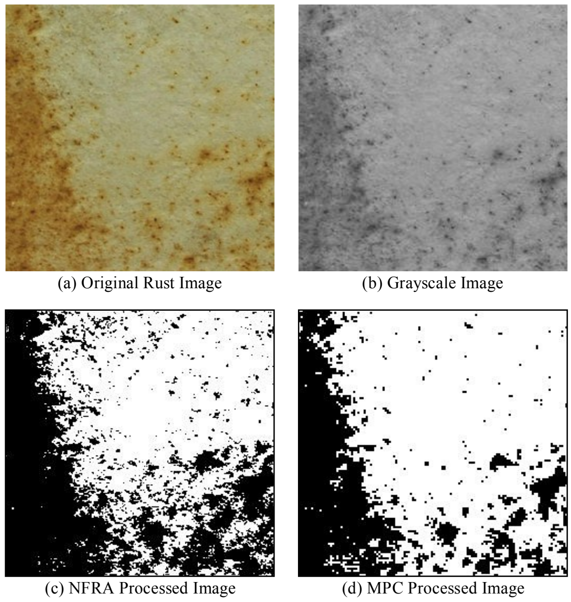

Figure 10. Comparison of NFRA and MPC (I)

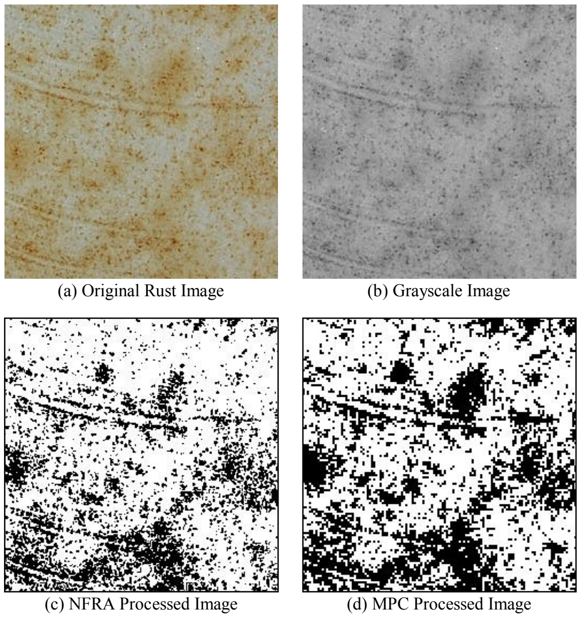

Figure 11. Comparison of NFRA and MPC (II)