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Intelligent diagnosis on bridge painting defects using image processing techniques

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Abstract

Up to now, most bridge painting inspection still relies on human visual diagnosis, which is subjective, less efficient and inaccurate. In order to shorten the evaluation time and increase the accuracy, an intelligent diagnosis system was developed with the hope to standardize and automate the evaluation process.

The system hybridizes image processing techniques and neural networks, which provide expert knowledge through training, to automatically diagnose the defects on an image. With the development of this system, vast number of images can be diagnosed instantly and intelligently.

1 Introduction

One of the major causes for the deficiencies of U.S. bridges is the deterioration of anti-corrosion coatings (Hunt [6]). In spite of the money spent, the effort to fix those deficiencies is progressing slowly, particularly in the area of coating quality assessment, a crucial element of steel bridge quality assurance. Moreover, the currently used assessment techniques are subjective, time consuming, and rely mostly on human visual inspection. These techniques have not taken advantage of advanced techniques, especially image processing technology (Shubinsky [10]; ASCE [1]). Such subjective assessment methods have been identified as a critical obstacle to effective infrastructure management (Hunt [6]). Therefore, more objective, accurate, and reliable assessment techniques need to be explored to improve the quality of infrastructure and constructed facilities.

This paper presents a computer-based decision support system for image processing in order to assist diagnosing the painting defects on steel bridges. The decision support model is the outcome of an undergoing joint research project

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between the Indiana Department of Transportation and Purdue University.

Image processing techniques enable the hybrid system to automatically diagnose the image, appropriately distinguish the defects from the background, and compute the percentage of the rusty area. Neural networks equip the system with expert knowledge based intelligence through the training of sample images. All these characteristics make the system capable of automatic diagnosis and decision making.

This paper first gives the basic concepts of image processing and neural networks, followed by the implementation of the intelligent diagnosis system through four modules; Data Acquisition, Preprocessing, Analysis, and Recognition. Finally, the conclusion is drawn.

2 Background

2.1 Image

Generally, an image is formed by means of visible light. The light emanates from a light source and interacts with the surfaces of objects. After that, part of the light is captured by an image formation system, like a camera, which produces a two-dimensional distribution of the light defined on the image plane. It is this distribution of light that we call an image (Looney [8]). The recognition of an object in an image is a complex process that involves a wide range of elaborate techniques. The first step in a typical image processing application is image acquisition, which is acquiring an image in digital format. The term "image" refers to a two-dimensional light intensity function $f(x,y)$ where x and y are geometrical coordinates and the value of f at any point (x,y) is proportional to the brightness or gray level of the image at that point. A digital image can be considered as a matrix in which each row and column represents a point in the image and the corresponding matrix element value represents the gray level at that point. The elements of such an array are called picture elements or pixels (Russ [9]; Weeks [12]).

2.2 Selection of threshold value

A critical domain of image processing is the segmentation of an image into different regions to separate the objects from the background. Thresholding is the operation of separating the image into different regions based upon its gray level distribution. Separation of the object pixel from the background pixels is accomplished by selecting a gray level value T such that all pixels within the image with f(x,y) > T will be classified as pixels belonging to the object (Russ [9]; Weeks [12]).

The goal of thresholding is to select a threshold value that separates an image into two distinct gray level groups:

$$h(x,y)=\begin{cases}GL_a \rightarrow f(x,y)\le T\\ GL_b \rightarrow f(x,y)>T\end{cases} \tag{1}$$

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Where GL_a and GL_b are the desired two gray levels in the thresholded image and $f(x,y)$ is the image function, which is proportional to the brightness or gray level of the image at the point (x,y). $h(x,y)$ is the modified image function after applying the threshold operation. The process of thresholding, as described in Equation (1), reduces an image with multiple gray levels to a two gray levels image containing gray levels of GL_a and GL_b. Typically, this two gray level image is referred to as a binary or binarized image (Weeks [12]).

Critical to the selection of a threshold value is an image's histogram, which is the count for the occurrence of each pixel value in the image to define the gray level distribution of its pixels (Russ [9]). Examining an image's histogram can instantaneously indicate the general location of best threshold value. The thresholding of a grayscale image is usually easy if the gray levels of the pixels defining an object are clearly separated from the gray levels defining the background. Under that condition, the histogram of the image will be bimodal, and the best threshold value is selected in the area between the two peaks. In a complex image, the gray levels of the objects may not be well separated, making the selection of the threshold value more complex (Russ [9]).

There are many adaptive thresholding methods that aspire to select a threshold value that either maximizes the information present in the thresholded image or attempts to minimize the error associated with the selection of a threshold value. One of the most popular adaptive thresholding algorithms is the optimum thresholding (Weeks [12]; Russ [9]).

Optimum thresholding algorithm is based upon a two-object model in which an image is separated into a set of object pixels and a set of background pixels (Bhanu [2]). Essentially, optimum thresholding assumes an image histogram that is bimodal, with a valley separating the two modal peaks. Optimum thresholding is based upon the Minimum Probability of Error (MPE) classifier model for signal processing used in the detection of a binary signal in the presence of a noise (Weeks [12]). Noise in an image can be defined as any external random factor, which affects the quality of an image such as camera motion, reflected light, etc. The MPE classifier model selects a threshold value that minimizes the error of detecting a 0 or 1 from a binary signal (Weeks [12]; Russ [9]). In the derivation of optimum thresholding it is not required that the frequency of gray levels for the background be equal to the distribution of gray levels for the object.

Let $O(GL_i)$ be the histogram for the object pixels and $B(GL_i)$ be the histogram for the background pixels. Figures 1 and 2 illustrate the two histograms of the distribution of gray levels for the background and the object. Thresholding these images with a value of T produces two errors. The first error is the misclassification of object pixels with gray levels below T as background pixels. This is shown in Figure 1 as the shaded area given by $E_1(T)$. The second error is the misclassification of background pixels with gray levels greater than T as object pixels. This error corresponds to the second shaded area $E_2(T)$ as shown in Figure 2.

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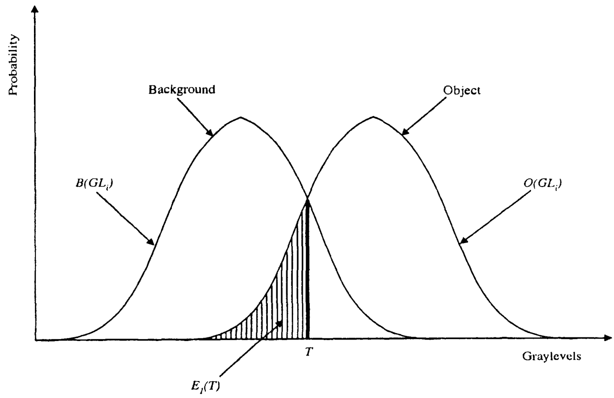

Figure 1: Error in object and background histogram (object error).

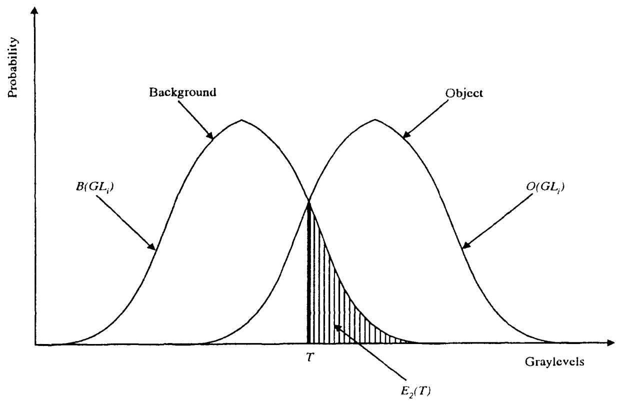

Figure 2: Error in object and background histogram (background error).

2.3 Neural networks

Tsoukalas and Uhrig defined an artificial neural network as: "A data processing system consisting of a large number of simple, highly interconnected processing elements (artificial neurons) in architecture inspired by the structure of the cerebral cortex of the brain (Tsoukalas [11])." The popular back-propagation neural network, which is a three-layered feed-forward architecture, is utilized in the developed hybrid system. A feed-forward network means a neuron's output can only originate from a lower level, and a neuron's output can only be passed to a higher level. The input layer receives the features of the data that are entered into the neural network. Figure 3 illustrates the basic structure of a feed-forward neural network (Haykin [5]).

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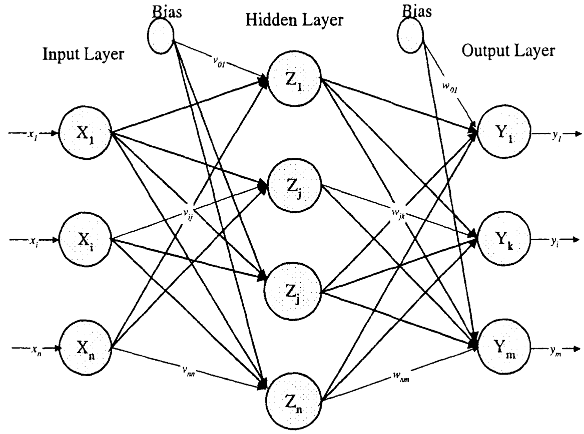

Figure 3: Neural network for the back-propagation algorithm.

Generally, neural networks are trained so that a particular input leads to a specific target output. The network is adjusted, based on a comparison of the output and the target, until the output matches the target (ASCE [1]; Haykin [5]; Kosko [7]; Tsoukalas [11]).

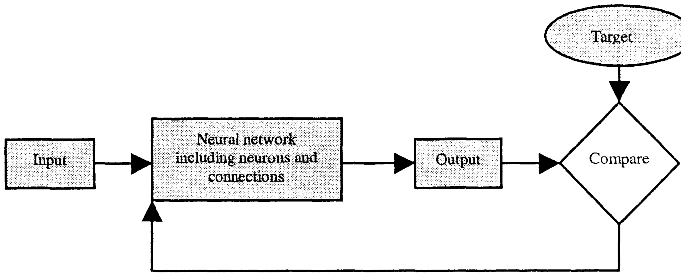

Figure 4: Neural network functionality.

A popular artificial neural network model is the back propagation network algorithm. The basic back propagation model is a three-layered feed-forward architecture. The first layer is the input layer, the second layer the hidden layer, and the third layer the output layer. Each layer contains a group of nodes that are linked together with nodes from other layers by connections among the nodes. Layers are connected only to the adjacent layers.

The input layer receives the features of the data that are entered into the neural network. If n feature values are to be entered into the input layer, then there must be n nodes, where n is the number of features supplied to the net. A single feature value is inputted into a single input node. The values are passed to the hidden layer through connections from the input layer. The nodes in the first layer distribute the individual inputs to all of the nodes in the hidden layer. The hidden layer acts as the connection between the input layer and the output layer. The main function of the hidden layer is to process the input data during the network training to connect to the output, i.e. to do the regression process in

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which the neural network tries to find correlation in the input data to predict the output (Haykin [5]).

3 Implementation

3.1 Data Acquisition

Several digital images of steel bridges coating were acquired using a Kodak DC-260 digital camera using two types of resolutions; 1536 x 1024 pixels and 1152 x 718 pixels. Many highway steel bridge coating images were taken at different locations in the state of Indiana. The model testing images were taken from the two steel bridges on Highway US-41 at the junction of Interstate I-74. The images were transferred to the computer using a Universal Serial Bus (USB) port and cable. Figure 5 shows sample images from the two bridges.

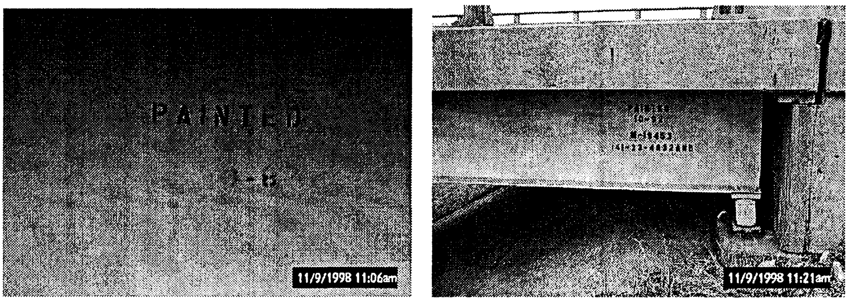

Figure 5: Sample coating images.

3.2 Pre-Processing

The images' quality is enhanced using different image processing techniques and filters such as noise reduction, contrast and brightness adjustments. Moreover, color images were converted to gray-scale for better threshold execution. Meanwhile, images are converted to numerical matrices for neural training and analysis.

Prior to the neural network training, image processing algorithms are applied for images' classification. The algorithms use pattern recognition for image classification into two classes or thresholding. Figure 6 shows a gray level image converted from an original color image (Chang [3], [4]).

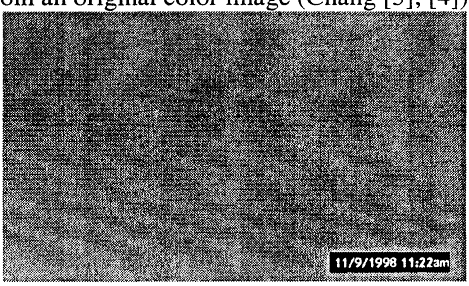

Figure 6: Graylevel example coating image.

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Figure 7 shows the original color image's histogram and Figure 8 shows the histogram for the image after it is converted to a gray scale image.

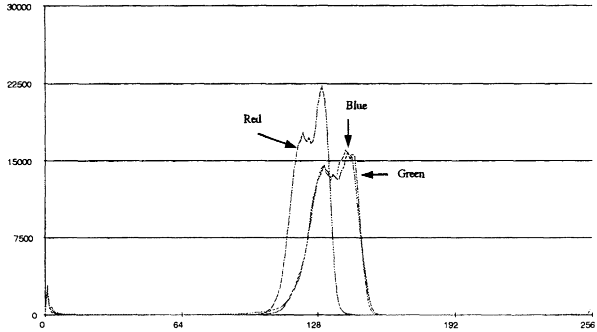

Figure 7: Original image's histogram.

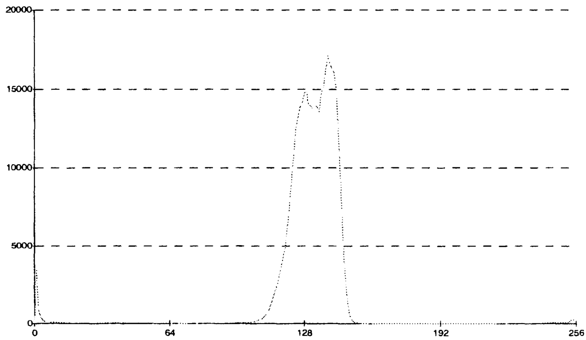

Figure 8: Gray scale image's histogram.

Figure 9 illustrates a thresholded image with object (rust) pixels recognized and labeled.

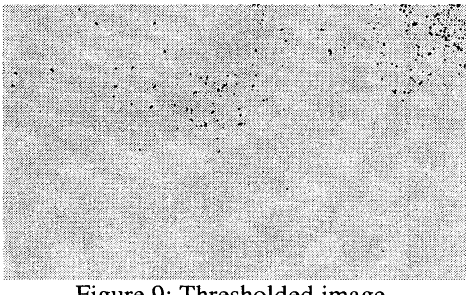

Figure 9: Thresholded image.

3.3 Analysis

In the next stage, images are passed to the neural network for training. A three-layer neural network with back-propagation training algorithm is used. The input layer consists of the gray levels of the coating image and the output layer

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consists of a mapped gray level value of 0 or 1. The total number of images used for training was 50. Figure 10 shows the neural network architecture.

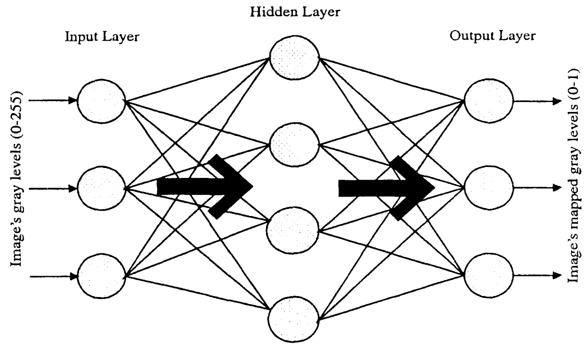

Figure 10: Neural network architecture.

A data set of 50 images was used to train the neural network. Each image pixel values matrix and mapped pixel values matrix was considered a training pair for the network. Figure 11 illustrates the training set for the neural network.

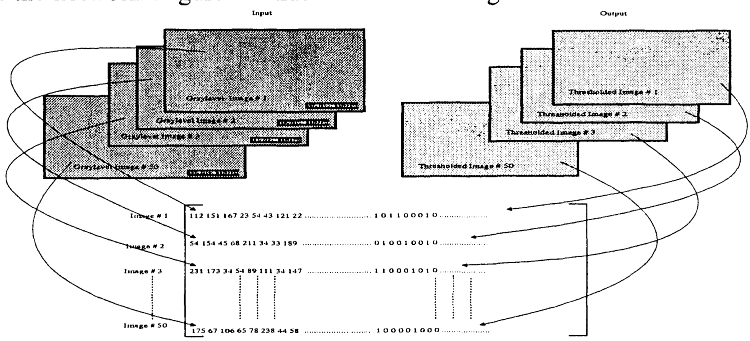

Figure 11: Neural network training set.

The aspiration of using the neural network is to generate reliable consistent assessment results even for noisy or lower quality images. The learning mode used is supervised learning so as to train the network from example images to simulate human experience in recognizing and classifying images with different parameters and different scenarios.

Prior to training, some human interference might be required, specifically in threshold selection for defect identification because of different parameters such as image quality, external factors in images such as dirt, etc. Adjustments are made using experts' knowledge and then the neural network is trained in order to automate the process in the future.

The neural network is relatively fault tolerant because it makes up for distorted or missing data provided that good training sets are provided. The reason behind that is the ability of neural networks to store knowledge in a distributed memory fashion among the network weights. Weights adjust repeatedly during training to reach minimum desired error. Because of the vast

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number of weights and the distribution of knowledge among them, incomplete or noisy data should not affect the accuracy of the network.

Neural network limitation stems from the fact that good sets of data should be provided for training. Training the network with distorted or misrepresenting data will generate inaccurate results and hence weaken the network's performance. Another limitation is the large amount of computing required to train images with high resolution. There is a trade-off between image resolution and computation efficiency. Moreover, The training set should include a full range of possible scenarios.

3.4 Recognition

Subsequent to the neural network training, more images were processed to obtain the pixels' mapping to 0 or 1 values and hence identification and measurement of defects (rust). Figure 12 illustrates the recognition procedure (Chang [3], [4]).

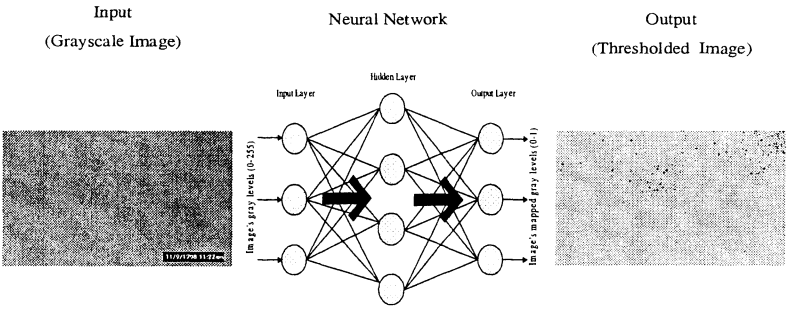

Figure 12. Recognition process.

The rust percentage area is calculated by counting the total number of rust pixels with value 1, from the neural network output, and dividing by the total image's number of pixels.

4 Conclusions

The system employs image processing and neural learning for coating defects diagnosis and measurement. This system overcomes the subjectivity and inconsistency of human visual assessment by analyzing digital images with computers. Unlike the human eyes, the computer can recognize and distinguish millions of colors and shades of gray, if the computer provides the capacity. By analyzing characteristics for each pixel in a given image, the model can recognize defect patterns undetectable by humans. Moreover, the system can measure the extent of defect with a reasonable accuracy.

This hybrid diagnosis system is expected to improve the quality assessment process by making the process more objective, quantitative, consistent, accurate, and efficient.

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