USING IMAGES PATTERN RECOGNITION AND NEURAL NETWORKS FOR COATING QUALITY ASSESSMENT

Image processing for quality assessment

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Abstract

Most current techniques used in construction and infrastructure assessment and quality inspection rely merely on subjective criteria. Such inaccurate or subjective assessment techniques have been identified as a critical obstacle to effective infrastructure or constructed facilities management. This paper illustrates a more objective and reliable assessment method to improve the conditions of the infrastructures or the quality of constructed facilities. The proposed system will automate the coating assessment process by using computers to analyze digital images of the areas to be assessed.

Keywords: Quality Assessment, image processing, pattern recognition, neural networks

1 Introduction

Bridge engineers and owners need accurate, consistent, and reliable information regarding paint system performance for the effective management and rehabilitation of bridges. Such information includes quantitative paint system ratings and accurate estimates of the useful life of the coating system. The extent of coating failure is most important in determining when a coating is to be repaired. Currently, the means available in the evaluation of coating performance is limited. Visual rating of the coating condition, which represents the most established technique, is plagued by a number of significant problems. It does not have the capability to provide accurate, quantitative, and consistent inspection data, thus precluding timely planning of bridge management and rehabilitation (Hsie and Chang 1995).

As well as being a safety hazard to the operator and traffic, the current visual inspection procedure is tedious, time-consuming, and subjective. All of the other available inspection methods are strictly localized, contact-point methods which are ineffective for assessment of global coating deterioration. Consequently, the infrastructure community has been looking for a more cost-effective, non-destructive instrument and methodology which would automate the repetitive visual inspection, improve the quality and reliability of inspection, and provide quantitative feedback regarding the paint condition (Chang and Carino 1998).

Therefore, to search for a better method for assessing bridge painting quality, a research project is exploring using computer visual image processing for painting quality assessment. Hopefully, this research can enhance the quality of assessment of steel bridge painting. The purpose of this paper is to present the framework for visual image processing research and its preliminary results.

2 Background

2.1 Prior research in computerized coatings assessment

There have been some similar research efforts performed at the Infrastructure Technology Institute (ITI) at Northwestern University (Shubinsky 1994). The main thrust of that research was the non-destructive evaluation of bridge coatings using several techniques, namely: Color Visible Imaging, Electrochemical Impedance Spectroscopy (EIS), and Infrared Imaging. Based on interviews conducted at ITI by the second author, the research result presented a generic framework, but was not developed to the implementation stage.

An experiment using visual imaging technique was devised for one bridge in order to obtain the amount of damaged areas due to rusting. Additional tests were performed on coated test panels inside the lab (could I have the reference please). One of the research conclusions and recommendations was to develop an applicable system, which should be portable and user-friendly. Moreover, one of the recommendations was to incorporate intelligence in the assessment system (Shubinsky 1994). The undergoing research by the authors is aiming to further explore the development of an applicable and intelligent system for bridge painting quality assessment.

2.2 Pattern recognition

Intelligent systems will be a dominant technology in the near future. Pattern Recognition (PR) techniques are often an important element of intelligent systems, and are used for both data processing and decision making. Broadly speaking, pattern recognition is the science that concerns the description or classification (recognition) of measurements. There is little doubt that PR is an important, useful, and rapidly developing technology with cross-disciplinary interest and participation. PR is not comprised of one approach, but rather is a broad body of often loosely-related knowledge and techniques (Schalkoff 1992).

Pattern recognition techniques assign a physical object or an event to one of several pre-specified categories or classes. Thus, a pattern recognition system can be viewed as an automatic decision rule; it transforms measurements on a pattern into class assignments. The patterns themselves can range from agricultural fields in a remotely sensed image from a satellite to a speech waveform or utterance from an individual. The associated recognition or classification problem could be to label an agricultural field as wheat or non-wheat or identify the spoken word. There are many algorithms for statistical pattern recognition. One of the most widely used algorithms is the K-Means algorithm (Ripely 1996).

2.2.1 The K-Means algorithm

The K-Means Algorithm self-organizes data to create clusters. This algorithm fits the coating inspection application well because of the number of clusters need to be predetermined, which is the case in the inspection process, are: defects and non-defects.

The algorithm uses a sample of feature vectors $V = \{x^{(1)}, \ldots, x^{(Y)}\}$ from a population P, but requires the number K of clusters to be given, $K < Y$. The process begins by assigning the first K sample feature vectors $x^{(1)}, \ldots, x^{(k)}$ to be centers $z^{(1)}, \ldots, z^{(K)}$, respectively, for the K clusters. The algorithm then assigns each of the remaining Y-K sample feature vectors $x^{(K+1)}, \ldots, x^{(Y)}$ to the cluster whose center is closest. Then, the sample feature vectors for each K^{th} cluster, in turn, are averaged to determine a new cluster center $z^{(K)}$ for each K^{th} cluster. Next, each of the Y sample feature vectors is again assigned to the class to whose new representative center it is closest.

This process of generating new centers by averaging each cluster and then reassigning all vectors by minimum distance to the new centers is repeated until no clusters change further, in which case the algorithm is finished (Ripely 1996).

2.3 Artificial neural networks

A popular artificial neural network model is the back propagation network model. The basic back propagation model is a three-layered 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 network is a feed-forward network, which means a unit's output can only originate from a lower level, and a unit's output can only be passed to a higher level. Figure 1 illustrates the basic structure of a feed forward neural network (Zurada 1992).

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 (Zurada 1992).

The connections between the layers are weighted to emphasize or de-emphasize the relative value of the input. The Input Layer does not operate on the feature data, but merely passes it to the Hidden Layer. Each node sums the *n* weighted inputs to the Hidden Layer. The value of the summation can be different for each node, due to differently weighted connections between the first and second layers. The values that are summed in the hidden nodes are then passed to the nodes in the Output Layer via another set of weighted connections. Each hidden node is connected with each output node. Although the Hidden Layer may actually consist of several Hidden Layers, some models' Hidden Layer uses only one layer.

The Output Layer generates the output of the neural network. In the same way the Hidden Layer functions, the Output Layer's input values are summed, and the summation becomes the output value. Each output node corresponds to a desired output class. Each node sums the *n* weighted inputs in the Hidden Layer and the values from each output node are compared to each other.

These weighted inputs are summed and used as the node output value. Several Output Layers can exist for a back propagation network. Because the back-propagation algorithm is an iterative algorithm, it can be trained by adjusting the connection weights among the nodes. The weights are recalculated after every complete cycle until the weights converge and the mean square error falls within the specified acceptable range.

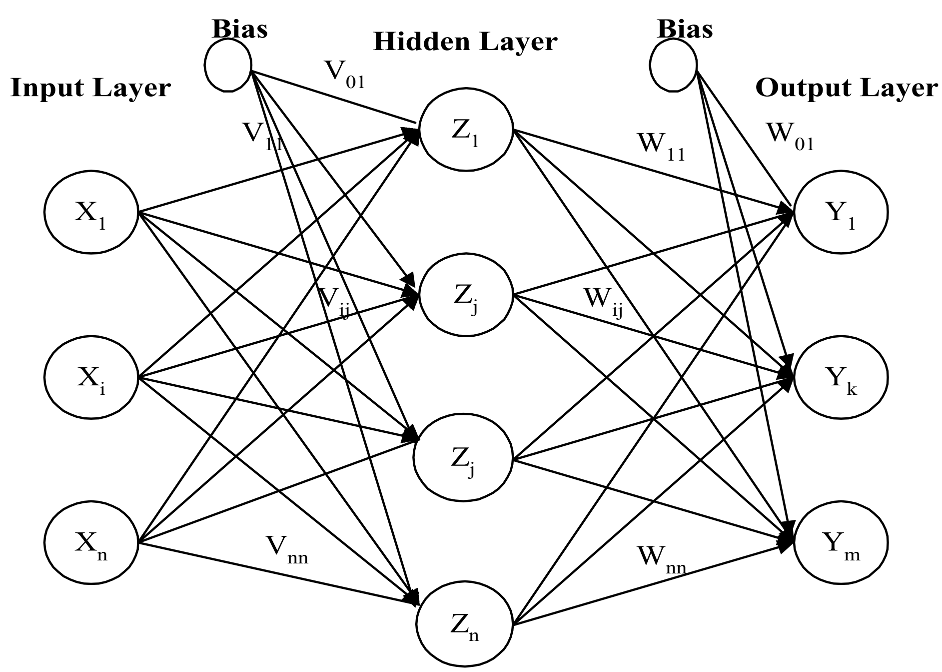

Fig. 1: Neural network for the back-propagation algorithm

3 Proposed assessment system

The basic concept of the decision support system is to obtain digital images of objects to be inspected and identify defects using image analysis techniques. Moreover, sample images will be used to train the system to acquire expert knowledge in identifying the defects and using this knowledge to later assess other coatings. Figure 2 illustrates the working system model. It consists of four main stages.

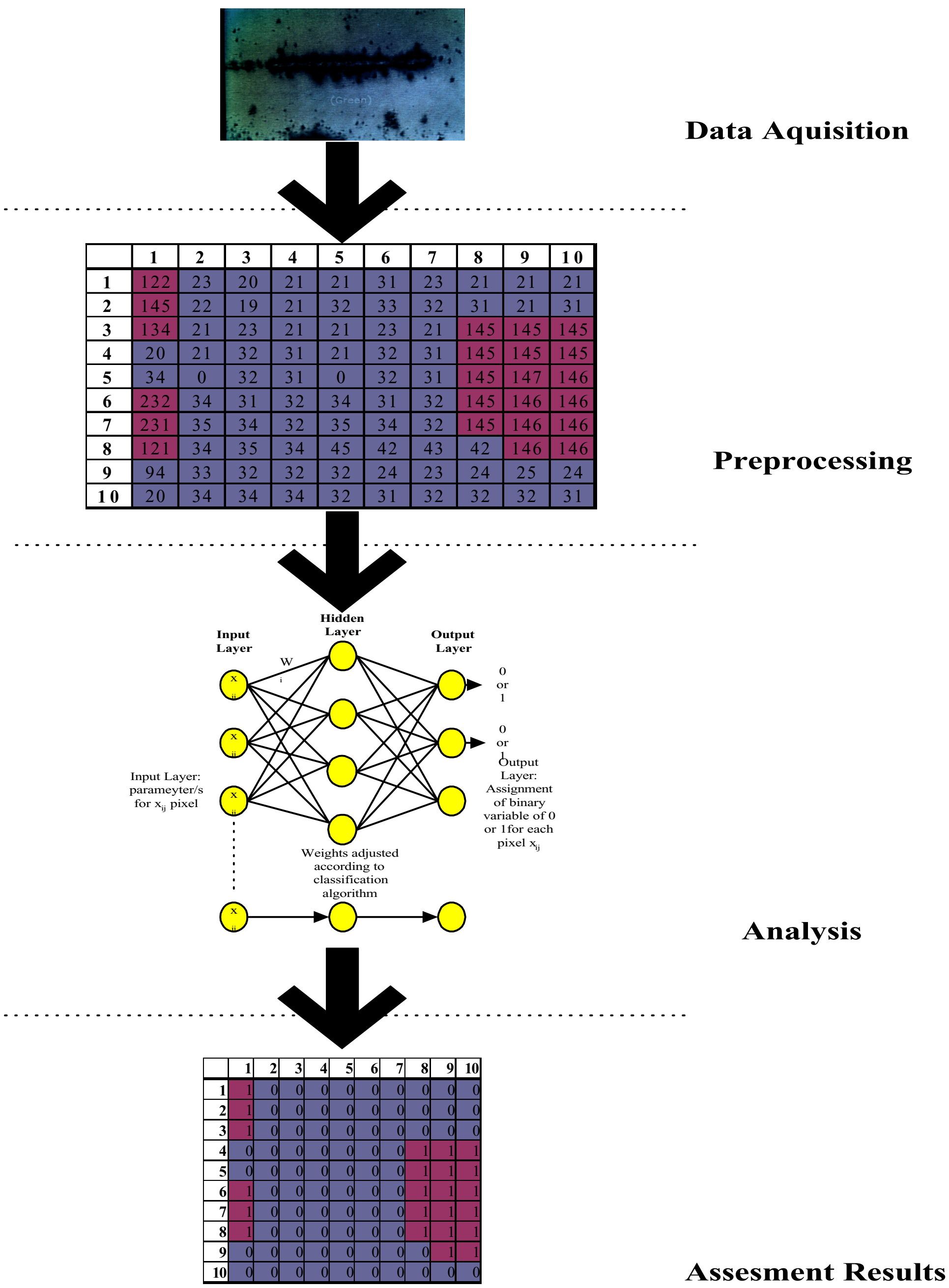

Fig. 2: Hybrid system model

The first stage is Data Acquisition: where digital images for the steel bridge coating (objects) are obtained using a digital camera. After acquisition the images are transferred to the computer on site or in a remote office via any communication protocol.

The next stage is the Preprocessing stage, where image analysis techniques are used to analyze and enhance the image by applying algorithms such as filtering and edge detection. Moreover, image pre-processing is used to obtain the numerical parameters of the image such as the gray level and brightness in a numerical format. At this stage a statistical pattern recognition algorithm is utilized to identify defects according to the numerical representation of images.

The next stage is the Processing stage. After being trained, neural networks are used to identify defects in the images by assigning binary variable of 0 or 1 for each pixel in the image. During the network training, the neural network is fed with different images and their parameters such as the pixels' gray levels. The network is also fed mapped values of 0 or 1 for each pixel value. The network will learn to assign the binary variable 0 or 1 for different scenarios according to image parameters.

The final stage is the Assessment Results stage, where quantitative measures of defects are obtained from the output of the previous stage. From mapped output of the neural network, the whole image is represented as 0's or 1's. The 1 values represent the defect; hence, defects can be identified and quantitatively measured. The system can be trained to identify different types of defects according to the specific application.

4 Example

The following example illustrates how a simple (5 pixel x 5 pixel) image could be used to illustrate the methodology of the hybrid system. Consider the image in Figure 3 to be an image of a part of steel bridge beam with a coating on. The darker areas represent defect object (rust) and the lighter areas represent background.

5	232	34	31	32	110
4	231	35	34	32	35
3	135	34	35	118	45
2	94	33	32	32	32
1	20	34	115	34	32
	1	**2**	**3**	**4**	**5**

Fig. 3: The image gray levels

Step 1 Data Acquisition

A digital image of a steel bridge coating area is obtained and transferred to the computer.

Step 2 Preprocessing

Image analysis software is used to enhance the image and to represent the image in numerical format. Figure 3 shows the sample image with the gray level shown for each pixel.

The next step is to apply the statistical pattern recognition algorithm to classify the numerical values into two clusters: rust or no rust. The result of this classification is then passed to the third step. K-Means algorithm is used for classification because it best fits this specific application in that the number of clusters to classify must be predetermined.

Given the data set obtained from the image numerical presentation in Figure 3, the K-means Algorithm is applied.

$$V = \{232, 34, 31, 32, 110, 231, 35, 34, 32, 35, 135, 34, 35, 118, 45, 94, 33, 32, 32, 32, 20, 34, 115, 34, 32\}$$

Using the K-Means Algorithm, the data set is classified into two classes: rust and non-rust pixels. After that, all pixels will be assigned a binary variable of 1 or 0, depending on whether it is a rust or non-rust pixel.

Select randomly, the first two samples as initial centers.

$z^1 = 232 \quad z^2=34$

Next assign each sample to the class with the closest center, i.e. to class 1 if it is closer to $z^1 = 232$ and to class 2 if it is closer to $z^2=34$.

The following table shows the difference between each pixel value and the initial two centers and hence to which class it is assigned. Note that the difference is calculated based on the gray level, not based on the location of the pixel. The gray level is considered a third dimension for each pixel.

Table 1: First iteration for K-Means algorithm

Pixel Value	Difference from z1	Difference from z2	Class 1	Class 2
232	0	198	x	
231	1	197	x	
135	97	101	x	
94	138	60		x
20	212	14		x
34	198	0		x
35	197	1		x
34	198	0		x
33	199	1		x
34	198	0		x
31	201	3		x
34	198	0		x
35	197	1		x
32	200	2		x
115	117	81		x
32	200	2		x
32	200	2		x
118	114	84		x
32	200	2		x
34	198	0		x
110	122	76		x
35	197	1		x
45	187	11		x
32	200	2		x
32	200	2		x

C_1 = {232, 231, 135}
C_2 = {34, 31, 32, 110, 35, 34, 32, 35, 34, 35, 118, 45, 94, 33, 32, 32, 32, 20, 34, 115, 34, 32}

Figure 4 shows the initial clustering.

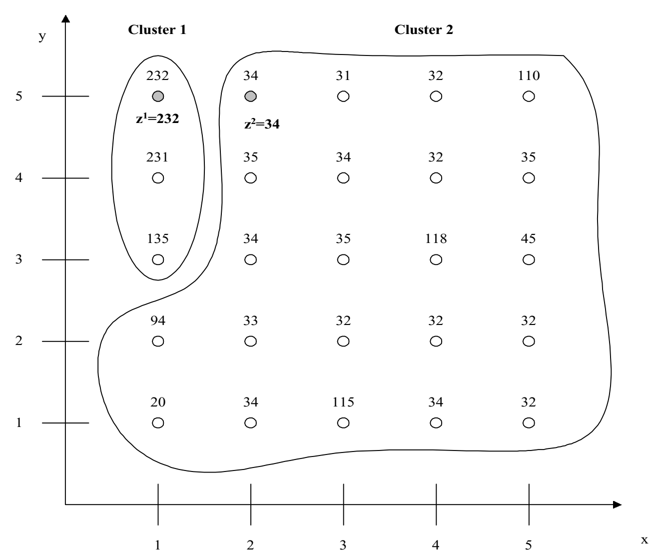

Fig. 4: Initial Clusters (With initial centers; z^1=232 and z^2 =34)

Next, each cluster's samples are averaged to obtain new optimal centers.

$$\text{New center } z^1 = \sum \frac{\text{Gray levels values in cluster 1}}{\text{number of points in cluster 1}} = 199.3$$

$$\text{New center } z^2 = \sum \frac{\text{Gray levels} \quad \text{in} \quad 2}{\text{of} \quad \text{in} \quad 2} =$$

The same procedure is applied again to find the distance between each sample

: Second iteration for K-Means algorithm

Pixel Value	Difference from z1	Difference from z2	Class1	Class 2
232	32.7	181.22	x	
231	31.7	180.22	x	
135	64.3	84.22	x	
94	105.3	43.22		x
20	179.3	30.78		x
34	165.3	16.78		x
35	164.3	15.78		x
34	165.3	16.78		x
33	166.3	17.78		x
34	165.3	16.78		x
31	168.3	19.78		x
34	165.3	16.78		x
35	164.3	15.78		x
32	167.3	18.78		x
115	84.3	64.22		x
32	167.3	18.78		x
32	167.3	18.78		x
118	81.3	67.22		x
32	167.3	18.78		x
34	165.3	16.78		x
110	89.3	59.22		x
35	164.3	15.78		x
45	154.3	5.78		x
32	167.3	18.78		x
32	167.3	18.78		x

$_1 = \{232, 231, 135\}$

C_2

34, 115, 34, 32}

final clusters are shown in Figure 5.

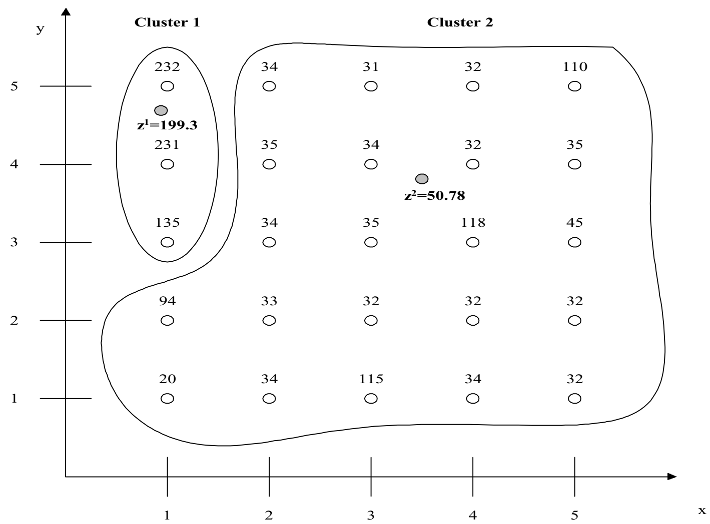

Fig. 5:Final Clusters

Finally, each sample is assigned a binary variable of 1 if it belongs to cluster 1 and 0 if it belongs to cluster 2. The image representation will be as shown in Figure 6.

5	1	0	0	0	0
4	1	0	0	0	0
3	1	0	0	0	0
2	0	0	0	0	0
1	0	0	0	0	0
	1	**2**	**3**	**4**	**5**

Fig. 6: Rust Identification in the Image

Step 3 Analysis

Data from the image shown in Figures 3 and 6 will be used to train the neural network. The purpose of using the neural network is to accommodate for errors that may occur when depending only on statistical pattern recognition. Adjustments are made using experts' knowledge and then the neural network is trained in order to automate the process in the future.

The complete neural network will consist of three layers: the input layer, the hidden layer, and the output layer. The input layer consists of the image data and has four elements: The x-axis location of the pixel, then the y-axis location of the pixel, the value of the gray level of the pixel, and finally the difference between the gray level of the pixel and a predetermined threshold value. The predetermined threshold value will be determined by experts' knowledge of coating inspection in coordination with results from image analysis. Another method for determining the threshold value is to apply image processing segmentation techniques. In this example, the predetermined threshold is 120. Table 3 shows the data entry for the neural network.

Table 3: Neural network data input

Input #	Location		Parameter 1	Parameter 2	Output
	(x)	(y)	(Grey Level)	(Difference from Pattern Threshold: 120)	(Binary Variable)
1	1	1	20	100	0
2	1	2	94	26	0
3	1	3	135	-15	1
4	1	4	231	-111	1
5	1	5	232	-112	1
6	2	1	34	86	0
7	2	2	33	87	0
8	2	3	34	86	0
9	2	4	35	85	0
10	2	5	34	86	0
11	3	1	115	5	0
12	3	2	32	88	0
13	3	3	35	85	0
14	3	4	34	86	0
15	3	5	31	89	0
16	4	1	34	86	0
17	4	2	32	88	0
18	4	3	118	2	0
19	4	4	32	88	0
20	4	5	32	88	0
21	5	1	32	88	0
22	5	2	32	88	0
23	5	3	45	75	0
24	5	4	31	89	0
25	5	5	110	10	0

Weights and biases are used by the network to emphasize or de-emphasize the importance of some data points. The initial values for weights and biases are chosen randomly but there are some guidelines for that choice. It is important to avoid choices of initial weights and biases that would make it likely that either activation or derivative of activation is zero. Also the value of weights and biases should not be too large, or the initial input signals to each hidden or output unit will be likely to fall in the saturation region, in which error can not be reduced.

5 Summary

A decision support system for steel bridge coatings assessment has been presented. The objective is to introduce the visual image processing on coating quality assessment. The image processing system uses the advanced technologies in the fields of machine learning, pattern recognition, and image analysis for steel bridges coating assessment. The basic concept of the research is to automate the assessment process by taking digital images of the rust areas and analyzing the images to identify and measure coating defects. The system will make the assessment process more objective, quantitative, and reliable.

6 References

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