2 BACKGROUND

2.1 Image Processing

One important goal of image processing is to segment the image into different regions to separate the objects from the background. In this paper, the critical technique used for segmentation is image thresholding, which employs a predefined gray level as decision criteria to separate an image into different regions based upon the gray levels of the pixels. Separation of the object pixels 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 1995; Weeks 1996), where x and y are spatial coordinates and $f(x,y)$, the image function, is proportional to the brightness or gray level at the point (x,y). Equation (1) shows the process of thresholding, where GL_a and GL_b are the desired two gray levels in the thresholded image and $h(x,y)$ is the modified image function after applying the threshold operation.

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

Thresholding reduces an image with multiple gray levels to a two-gray-level image containing gray levels of the object and the background. Typically, this two-gray-level image is referred to as a binary or binarized image (Weeks 1996).

When there are more than two distinct regions, a better method would be to use multi-level thresholding. The approach taken by multilevel thresholding is to expand Equation (1) to include more than one threshold value as follows:

$$h(x,y) = \begin{cases} GL_a \rightarrow 0 \le f(x,y) < T_1 \\ GL_b \rightarrow T_1 \le f(x,y) < T_2 \\ GL_c \rightarrow T_2 \le f(x,y) < GL_{\max} \end{cases} \qquad (2)$$

Where GL_{max} is the maximum gray level of the image $f(x,y)$. Equation (2) segments the image into three gray level regions, GL_a, GL_b, and GL_c depending on two threshold values, T_1 and T_2. 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. 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 1995).

Associated with the selection of a threshold value is an image's histogram, which counts the frequencies of the happenings of different gray levels within an image (Russ 1995). Examining an image's histogram can instantaneously indicate the general location of the best threshold value. One of the most popular adaptive thresholding algorithms is optimum thresholding (Weeks 1996; Russ 1995), which is essentially a two-object model with an image being separated into a set of object pixels and a set of background pixels (Bhanu and Lee 1994).

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 1996). Noise in an image can be defined as any external random factor that affects the quality of an image such as camera motion, reflected light, and so forth. The MPE classifier model selects a threshold value that minimizes the error of detecting a 0 or 1 from a binary signal (Weeks 1996; Russ 1995).

Let P_o be the probability of an object in an image and P_b be the probability of the background; then

$$P_o = \frac{n_o}{n_t} \qquad (3)$$

$$P_b = \frac{n_b}{n_t} \qquad (4)$$

Where n_o is the number of object pixels, n_b is the number of background pixels, and n_t is the total number of pixels in the image. The sum of the two probabilities must add up to one, since the assumption is that only object and background pixels are present within the image. 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.

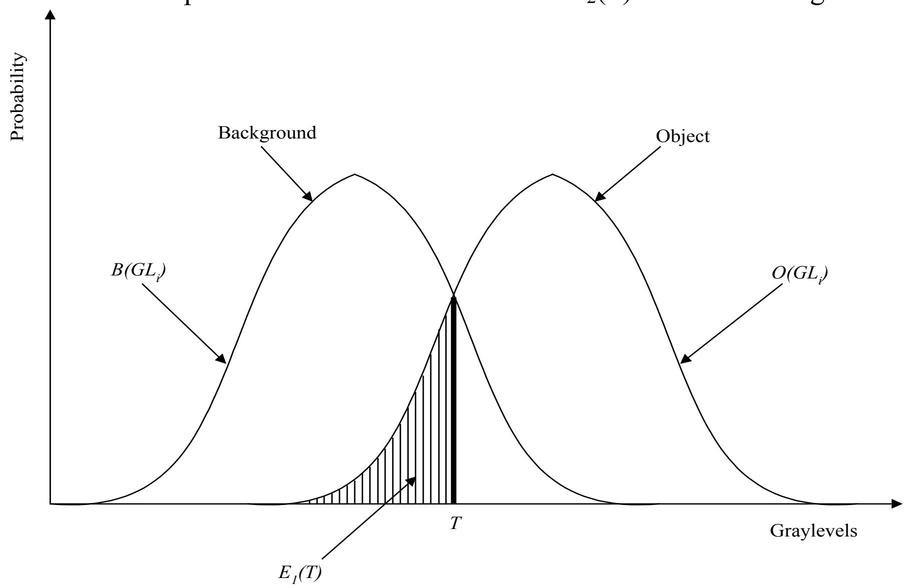


Figure 1. Error in Object and Background Histogram (Object Error)

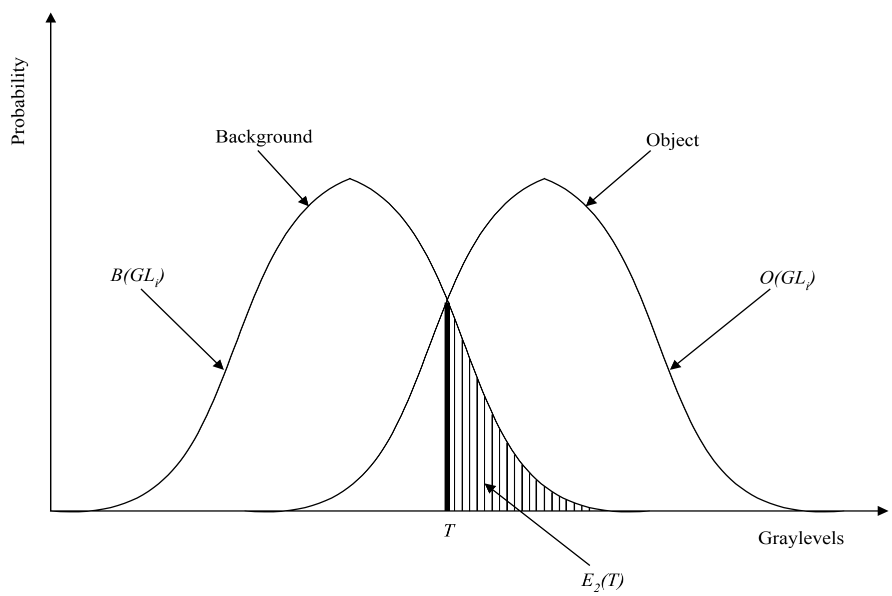


Figure 2. Error in Object and Background Histogram (Background Error)

2.2 Artificial 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 and Uhrig 1997)." 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 1999).

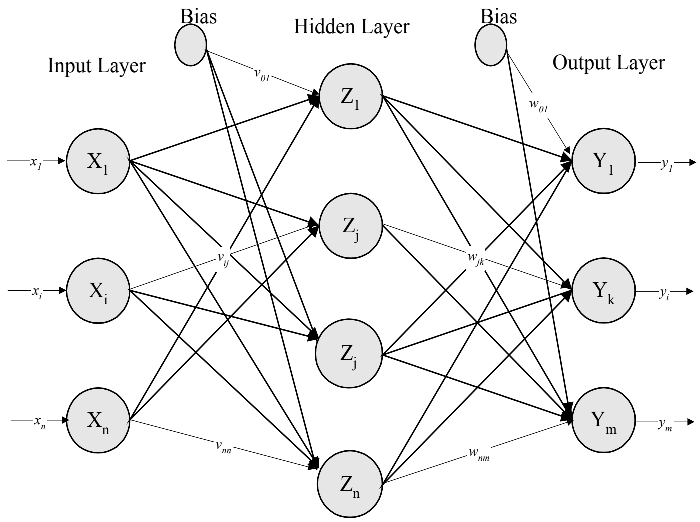


Figure 3. Neural Network for the Back-Propagation Algorithm

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 which the neural network tries to find correlation in the input data to predict the output (Haykin 1999).

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 1997; Haykin 1999; Kosko 1992; Tsoukalas and Uhrig 1997).

3 SAMPLING PLAN

Owing to limited time and budget, it is usually unlikely to take images of a whole bridge when conducting bridge painting inspection. In order to unbiasedly select image samples, two random sampling plans were developed based on statistical theories.

3.1 Random Sampling Plan I

1) *Details of the bridge to be inspected:* The numbers of beams and diaphragms should be known before the start of the sampling procedure.
2) *Coding:* Steel beams and diaphragms are numbers according to their geographical direction starting at the top left corner, as shown in Figure 4.

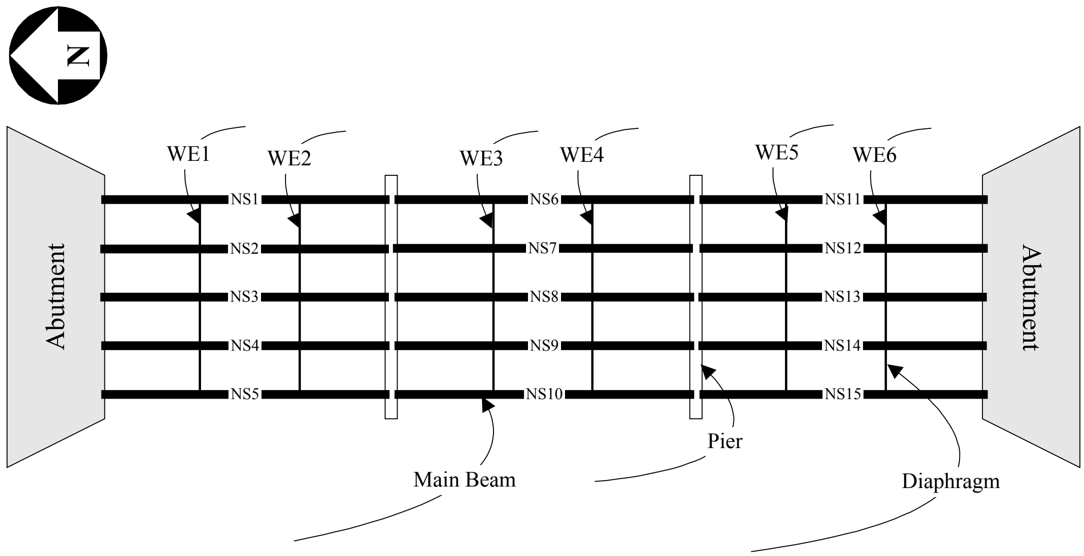


Figure 4. Coding of Beams and Diaphragms

3) *Sampling table:* After the coding is finished, a detailed sampling table should be made for the convenience of random sampling. In the sampling table, all coded beams and diaphragms are numbered sequentially based on "sections." In the picture shown, there are three sections in each beam and four sections in each diaphragm. The way of numbering sections also starts from the top left corner with diaphragms numbered after beams. In the picture, there are 15 beams and 6 diaphragms. Therefore, the numbers of beam sections start from 1 to 45, and the numbers of diaphragm sections are from 46 to 69. Figure 5 illustrates the section-based coding and Table 1 demonstrates the basic sampling table. To make a more accurate sampling table, users can number both sides of each section and the total number will double.

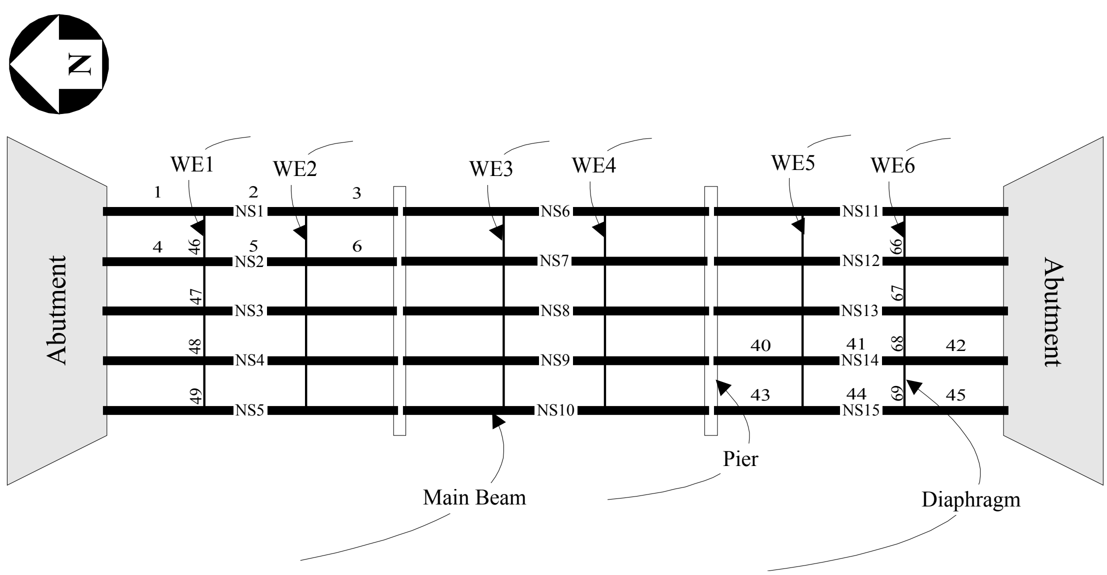


Figure 5. Section-based Coding of Beams and Diaphragms

Number	***Beam/Diaphragm***	***Number***	***Beam/Diaphragm***
1	NS1	46	WE1
2	NS1	47	WE1
3	NS1	48	WE1
4	NS2	49	WE1
5	NS2	50	WE2
⋮	⋮	⋮	⋮
42	NS14	66	WE6
43	NS15	67	WE6
44	NS15	68	WE6
45	NS15	69	WE6

Table 1. Sampling Table

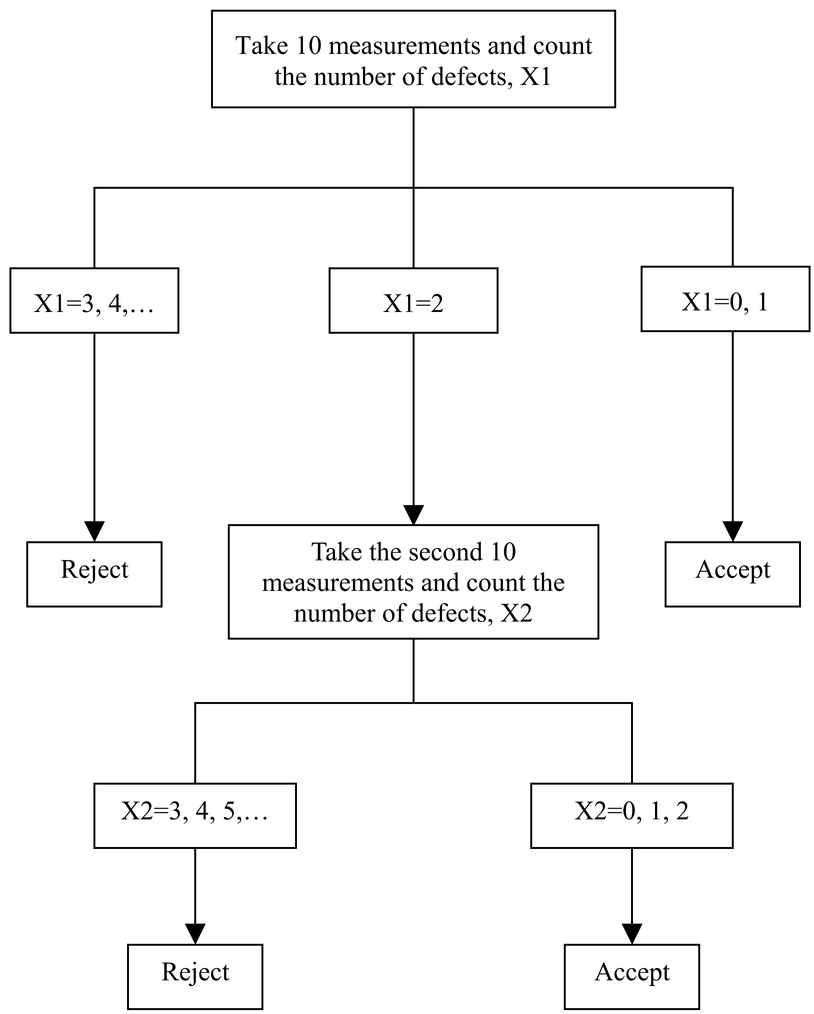


Figure 6. Flow of Double Sampling Plan

4) *Sampling plan:* The double sampling plan is adopted for acceptance assessment. Figure 6 illustrates the flow of the double sampling plan. The inspector first takes 10 samples and counts

the number of defects. If the defect number is 0 or 1, the painting work of the bridge is accepted. If the defect number is equal to or larger than 3, the painting work is rejected. If the defect number is equal to 2, a second set of 10 samples should be taken. In the second set of samples, if the defect number is 0, 1, or 2, the painting work is accepted. If the defect number is equal to or larger than 3, the painting work is rejected.

5) *Random sampling:* The random number generator, which evenly generates random numbers between 0 and 1, is used for random sampling. A random number could be 0 but has to be less than 1. A random number could be converted to a section number by the following equation:

   *Section Number = [Random Number * 100 * (N / 100)]*
   *= [Random Number * N] ,*
   where [ ] is a rounding operator, and N indicates the total section number.

   In this case, N is equal to 69. The first set of 10 samples can be selected by taking the first 10 different section numbers generated by the random number generator. If a second set is required, it can be generated in the same way.
6) *Image acquisition:* After the section numbers are determined, images are taken with a digital camera that is positioned three feet from the sections. To ensure all the image samples have similar brightness, the flash should be switched on throughout the image-taking process.

3.2 Random Sampling Plan II

In the second random sampling plan, the bridge demonstrated is assumed to be built on a four-lane highway, with two lanes in each direction. For bridges built above a different number of lanes, the sampling procedure could be modified accordingly.

1) *Selecting lanes.* Based on the centerline of the bridge and the lane lines on both sides, the whole bridge can be broken into four sections: sections I, II, III and IV, as shown in Figure 7. Sections I and III belong to one group, and sections II and IV belong to the other. Images can be taken randomly from either I and III, or II and IV.

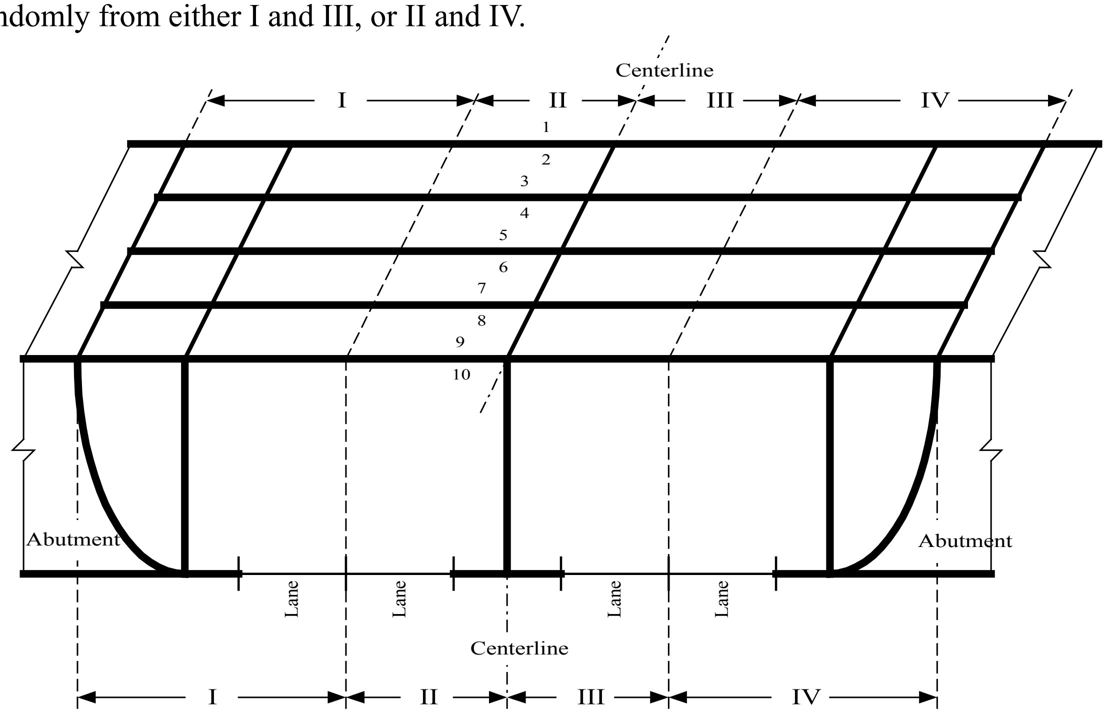


Figure 7. Bridge Segmentation

2) *Deciding lots*. Each side of a beam in a section is defined as a lot (as shown in Figure 7). There are two lots for each beam within a selected section. If there are four beams in a section, eight lots are contained in this section. Ten lots are selected from each of the two sections in the group chosen. If the number of lots in a section is larger than ten, ten lots are randomly selected from this section. If the number of lots is ten, images are taken directly from the ten lots without using the random selection process. If the number of lots in a section is less than ten, all lots are chosen, plus random selections are made on the difference between ten and the lot number in this section. For example, if eight lots are in a section, all eight lots are selected. Additionally, two lots out of the eight are randomly selected.
3) *Taking images*. Each lot is broken into five locations and three images are taken from each location. Figure 8 depicts the five locations. There are fifteen images taken from each lot, and thirty images taken from a beam in a section.

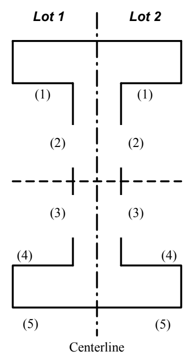


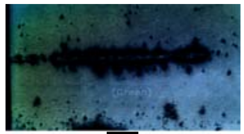
Figure 8. Locations in a Lot

4 THE RECOGNITION SYSTEM

The concept of the hybrid system is to acquire digital images of objects to be assessed and identify defects by using image-processing techniques. To make the system "intelligent," expert knowledge is combined with the system through the training of sample images. Figure 9 illustrates the architecture of the hybrid system.

The first module is Data Acquisition, where digital images of the constructed facility (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. This module is illustrated in Figure 10.

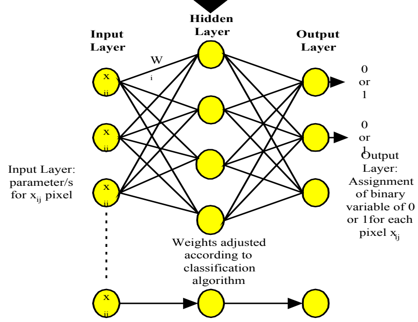
The next stage is the Preprocessing module, where image analysis techniques may be used to analyze and enhance the image by applying algorithms that will filter and reduce noise. Moreover, image pre-processing is used to obtain the parameters of the image, such as the gray level in a numerical format. At this stage statistical pattern recognition and image segmentation algorithms are utilized to identify defects according to the numerical representation of images. Figure 11 illustrates the Preprocessing module.



Data Acquisition Module

	1	2	3	4	5	6	7	8	9	10
1	122	23	20	21	21	31	23	21	21	21
2	145	22	19	21	32	33	32	31	21	31
3	134	21	23	21	21	23	21	145	145	145
4	20	21	32	31	21	32	31	145	145	145
5	34	0	32	31	0	32	31	145	147	146
6	232	34	31	32	34	31	32	145	146	146
7	231	35	34	32	35	34	32	145	146	146
8	121	34	35	34	45	42	43	42	146	146
9	94	33	32	32	32	24	23	24	25	24
10	20	34	34	34	32	31	32	32	32	31

Preprocessing Module



Analysis Module

	1	2	3	4	5	6	7	8	9	10
1	1	0	0	0	0	0	0	0	0	0
2	1	0	0	0	0	0	0	0	0	0
3	1	0	0	0	0	0	0	1	1	1
4	0	0	0	0	0	0	0	1	1	1
5	0	0	0	0	0	0	0	1	1	1
6	1	0	0	0	0	0	0	1	1	1
7	1	0	0	0	0	0	0	1	1	1
8	1	0	0	0	0	0	0	0	1	1
9	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0

Recognition Module

Figure 9. The Hybrid Diagnosis System Architecture

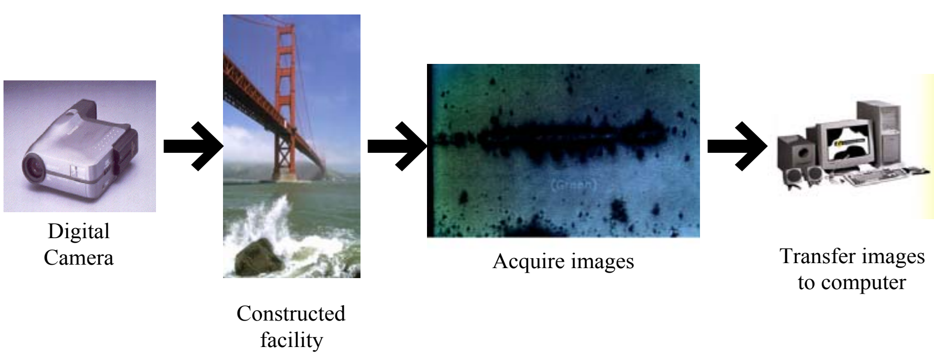


Figure 10. Data Acquisition Module

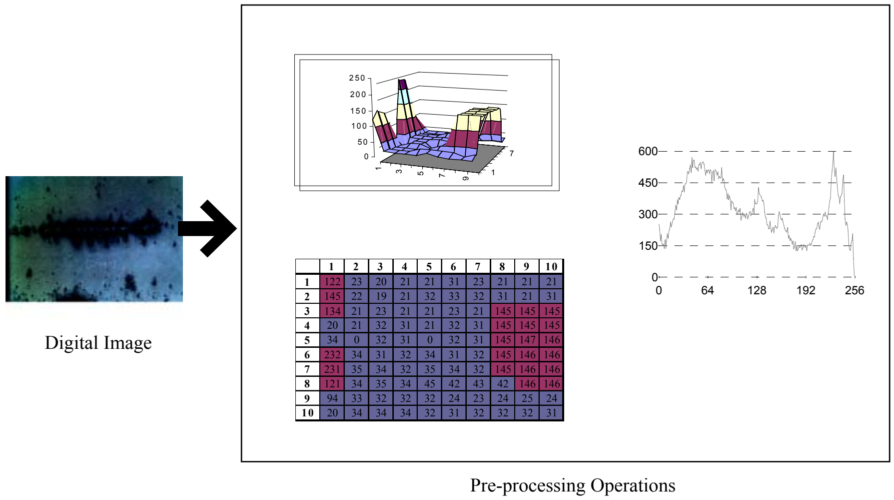


Figure 11. Pre-processing Module

The next module is the Analysis. After being trained, neural networks are used to identify defects in 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 supplied mapped values of 0 or 1 for each pixel value depending on whether it is defect or not. The network will learn to assign the binary variable 0 or 1 for different scenarios according to image parameters. Figure 12 illustrates the analysis module.

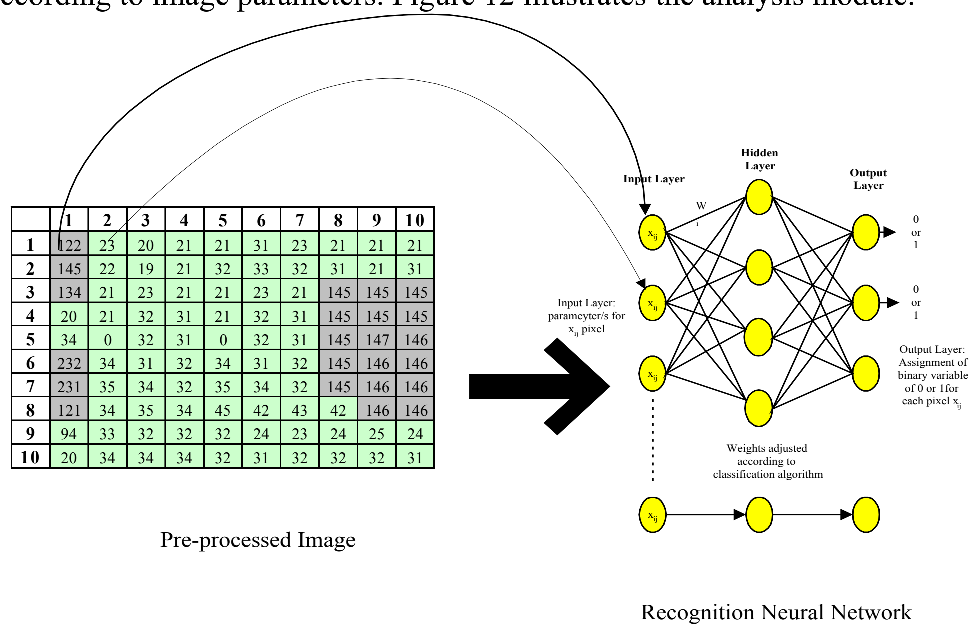


Figure 12. Analysis Module

The final stage is the Recognition module, where quantitative measures of defects are obtained from the output of the previous stage. From the mapped output of the neural network, the whole image is represented as 0's or 1's. The 1 values represent the defects; hence, defects can be identified and quantitatively measured as a percentage of the whole area. The system can be trained to identify different types of defects according to the specific application. The recognition module is shown in Figure 13.

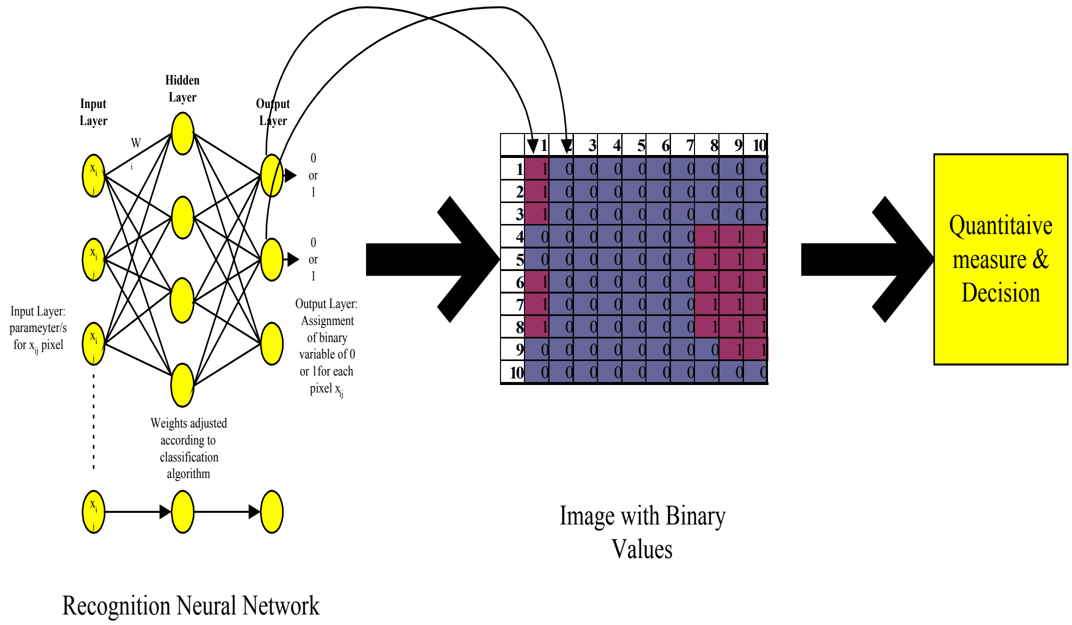


Figure 13. Recognition Module.

5 CONCLUSIONS

This paper presents two unbiased sampling plans for image acquisition and a recognition system for the quality assessment of steel bridge surface rusts. The two sampling plans help to select representative locations for image acquisition. The recognition system employs image processing and neural learning for surface defect diagnosis and measurement. The main purpose is to provide an automated defect diagnosis system that is objective, quantitative, consistent, and reliable.

This system overcomes the subjectivity and inconsistency of human visual assessment by analyzing digital images with computers. Unlike the human eye, the computer can recognize and distinguish millions of colors and 256 shades of gray. 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.

Nevertheless, human expertise can be integrated in the system, specifically during the images' threshold selection for classification, to accommodate for external factors such as the images' quality and the existence of dirt or drippings on the coating. Neural networks enable the system to learn from examples in order to automatically perform the diagnosis task after training.

The developed recognition system is expected to expedite the defects detection process with comparatively higher degree of accuracy.

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