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BOX-AND-ELLIPSE-BASED NEURO-FUZZY APPROACH FOR BRIDGE COATING ASSESSMENT

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ABSTRACT: Image processing has been utilized for assessment of infrastructure surface coating conditions for years. However, there is no robust method to overcome the non-uniform illumination problem to date. Therefore, this paper aims to deal with non-uniform illumination problems for bridge coating assessment and to achieve automated rust intensity recognition. This paper starts with selection of the best color configuration for non-uniformly illuminated rust image segmentation. The adaptive-network-based fuzzy inference system (ANFIS) is adopted as the framework to develop the new model, the box-and-ellipse-based neuro-fuzzy approach (BENFA). Finally, the performance of BENFA is compared to the Fuzzy C-Means (FCM) method, which is often used in image recognition, to show the advantage and robustness of BENFA.

Keywords: Bridge coating defect recognition, image processing, adaptive-network-based fuzzy inference system (ANFIS), Fuzzy C-Means

1. INTRODUCTION

Conventional steel bridge surface defect assessment is carried out by engineer's visual inspection which is time and cost wasting and inconsistent. With the prevalence of computerized technologies, digital image processing has been used in this field [1]. Computerized assessment provides consistent, accurate, quick, and objective results.

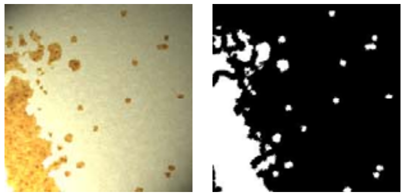
In previous studies, most of the images were processed in grayscale which could not deal with non-uniform illuminated images well [1-3]. Although Lee (2005) proposed a model by color image processing, its threshold should be determined in advanced. Therefore, this paper aims to solve non-uniform illumination problem and to automate the recognition. The first step is to select the best color coordinate system from 14 existing color spaces. The adaptive-network-based fuzzy inference system (ANFIS) is adopted as the frame work to develop the new method, the box-and-ellipse-based neuro-fuzzy approach (BENFA). Illumination adjustment is also adopted in this approach to overcome the non-uniform illumination problem. The BENFA could recognize the rust intensity in terms of serious rust percentage area and mild rust percentage area. Finally, the performance of the BENFA is compared to the Fuzzy C-Means (FCM), one of the most popular image recognition methods [4], to show its superiority and stability of rust intensity recognition.

2. SELECTION OF THE BEST COLOR CONFIGURATION

To color image processing, one of the most important issues is to select the best color coordinate. Process an image by the same algorithm in different color coordinates may get different results. Therefore, this paper starts with selection of the best color configuration. A color configuration is a component or a combination of the three components of a color space [5]. The following 14 color spaces will be investigated in this paper: RGB, rgb, I1I2I3, HSV, HSI, YUV, YIQ, YCbCr, YCgCr, XYZ, W*U*V*, L*u*v*, L*a*b*, and L*C*h* [5-7].

2.1 Artificial Rust Images

In order to evaluate the accuracy of the segmentation results, artificial rust images are introduced in this section. By means of copy and paste in the blank image, an artificial rust image could be made. In order to evaluate the performance of filtering light, artificial image with non-uniformly illuminated image as shown in Fig.1 should be made. Since the rust area could be ensured from the map (Fig.1(b)), the segmentation results could be evaluated in terms of error.



(a) Artificial rust image

(b) Map White: rust Black: coating

Figure1. Artificial rust image

2.2 The K-Means Algorithm

The clustering criterion of the K-Means algorithm is based on the distances between data points and cluster means. A data point will be classified to the cluster whose cluster mean has the shortest distance to the data point. The number of clusters should be determined in advance. In fact, the symbol K refers to the number of clusters. Therefore, in this paper, the K value would be two: one cluster is rust and the other is background. The K cluster means are selected such that the sum of the distances from the cluster mean to each data point in the cluster is the least. Generally speaking, the K-Means algorithm could be broken down into the following steps:

1. Randomly select K data points as the initial cluster means (or cluster centers);
2. Assign each of the remaining (N-K) data points to the closest cluster based on the distance between the data point and the cluster mean, given that N is the total number of data points;
3. Re-calculate the mean of each cluster (and set it as the new cluster center);
4. Repeat Steps 2 and 3 until no more change to the clustering result.

2.3 Evaluation of the color configurations using the K-Means

Since the K-Means algorithm is regarded as a simple and effective clustering method [3], it is used to select the best color configuration. Through clustering 10 uniformly and 40 non-uniformly illuminated rust images, the best color configurations are shown in Table 1.

Table 1. The color configurations whose accuracy is all higher than 90%

Color space	
W*U*V*	W*U*V*, U*, W*U*, U*V*
L*u*v*	L*u*v*, u*, L*u*, u*v*
L*a*b*	L*a*b*, a*b*

The L*a*b* color space is defined from Equation 1 to 4. Since the denominator is reference white which is a non-zero value, the L*a*b* color space does not have singular problem, while the W*U*V* and L*u*v* may have the singular problem. Therefore, the L*a*b* is considered as the best color space. Finally, the a*b* color configuration is selected to develop the following work due to its low dimension.

$$L^* = 116\, f\left(\frac{Y}{Y0}\right) - 16 \tag{1}$$

$$a^* = 500\left[f\left(\frac{X}{X0}\right) - f\left(\frac{Y}{Y0}\right)\right] \tag{2}$$

$$b^* = 200\left[f\left(\frac{Y}{Y0}\right) - f\left(\frac{Z}{Z0}\right)\right] \tag{3}$$

$$f(x) = \begin{cases} x^{\frac{1}{3}}, & \text{if } x > 0.008856 \\ 7.787x + \frac{16}{116}, & \text{otherwise} \end{cases} \tag{4}$$

3. IMAGE PREPROCESSING

The image preprocessing includes automated detection of background, illumination adjustment, and definition of the rust color by fundamental ellipse.

3.1 Automated Detection of Background

Through observation of several rust images, we found out that the rust colors are more complicate (include serious rust and mild rust) while the background colors are relatively condensed. The fact motivates this paper to start with background color elimination, since the background color is relatively simple. It has to acknowledge that this method cannot deal with the bridge with brown color paint, since the discriminating criteria is based on chroma (brown or non-brown).

In order to define the area of background color on the a*b* plane, this section aims to automatically extract a background area from a rust image. In general, the extraction is based on cutting and selecting, and it could be broken down to the following steps:

1. Divide an image into four equal parts.
2. Select the part whose color mean to the previous define rust color is the farthest.
3. Calculate the color entropy En of the part, where P(a*, b*) is the probability that will produce the color (a*, b*).

$$En(a^*, b^*) = -\sum P(a^*, b^*) \log_2 P(a^*, b^*) \tag{5}$$

4. Repeat the step1 to step 3 until the entropy is smaller than 2.5 or the size of the area is smaller than 10*10.

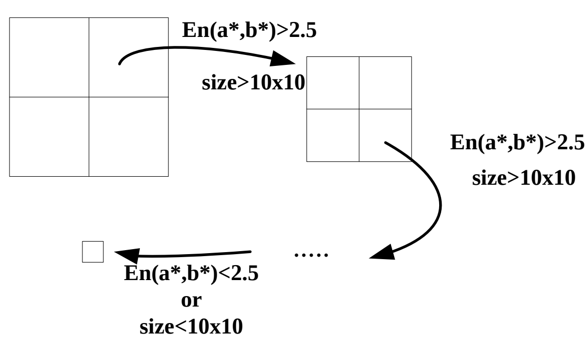


Figure2. Process of automated detection of background

Fig. 2 presents the process. The termination condition is set based on the analysis of rust images. Most of the entropy of the background texture is below 2.5. Also, in order to define an area of background color, the limitation of the divided size is necessary. Therefore, another terminal criterion ensures the size of the detected background.

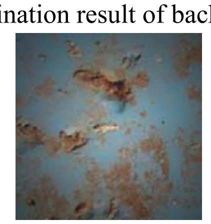
3.2 Illumination Adjustment

Non-uniform illumination has always been a challenge in image processing. However, this effect should be considered in this paper, since shade and shadow may exist on the bridge surface. The proposed illumination adjustment aims to include the effect of non-uniform illumination.

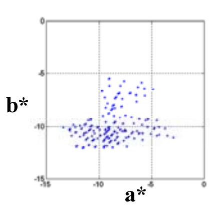
Illumination adjustment is processed in the RGB color space and is used to adjust the light intensity (or illumination) of rust images so that the light effect on background colors could be better studied and handled. In the RGB color space, a color will remain the same after multiplying or dividing the three components (R/G/B) by a constant[8]. Therefore, it is easier to do intensity adjustment in the RGB color space.

In the RGB color space, a color will remain the same after multiplying or dividing the three components (R/G/B) by a constant[8]. Through trials and errors, it is found that the light effect on the background color could be moderately mitigated if the values of the three components (R/G/B) of the background color could be reduced to at least 100 or increased to 255, out of the range of [0, 255]. Therefore, the illumination adjustment is proposed as: (1) identify the largest value (denoted as x) among the three components (R/G/B) of the background color; and (2) multiply the three background color components by (100/x) or by (255/x).

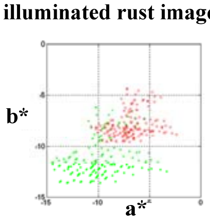
Through automated background color detection and illumination adjustment, the complete definition of the background color (with different light intensities considered) could be obtained. This background colors are approximated by the box shape determined by the extrema value of the background colors. Fig. 3 shows the elimination result of background colors.



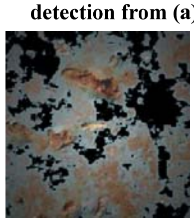
(a) Non-uniformly illuminated rust image



(b) Automated background detection from (a)



(c) Illumination adjustment from (b)

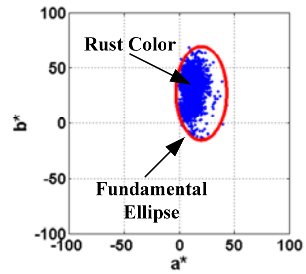


(d) Elimination of background

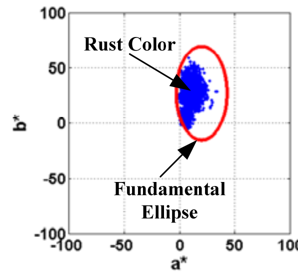
Figure 3. Result of background elimination after illumination adjustment

3.3 Definition of rust color by the fundamental ellipse

By observation of several rust images, we can find out that most of the rust colors are in brown tone. In order to effectively catch the rust color, this section aims to approximate the rust color in advance.



(a) Scatter of rust colors on the a*b* plane without illumination adjustment



(b) Scatter of rust colors on the a*b* plane with illumination adjustment

Figure 4. Rust colors and the fundamental ellipse

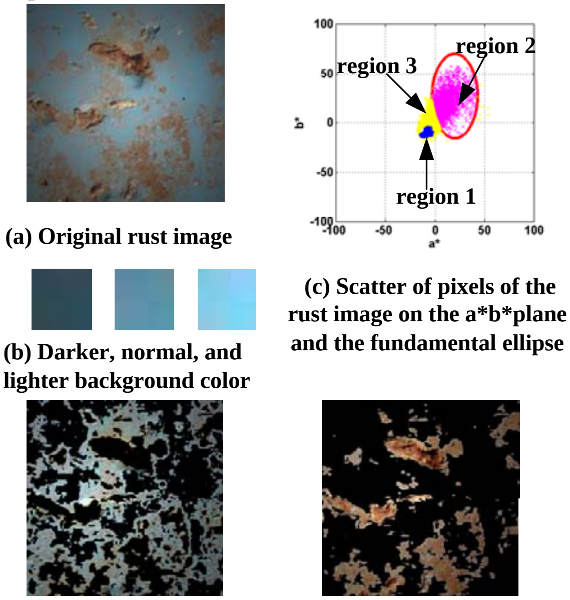
The scatter of the rust color in Fig. 4 looks like an ellipse. In 2000 Adachi et al. proposed to use an ellipse to approximate the flesh color on the UV plane, which is one of the color configurations of the LUV color space, for face detection [9]. The previous work motivates this paper to approximate the rust color by ellipse. This paper defines the area of rust color tones on the a*b* plane using an ellipse, called the fundamental ellipse as shown in Fig. 4. The fundamental ellipse is defined according to all the collected rust colors, as shown in Fig. 4(a). Since non-uniform illumination is always an important issue, illumination adjustment is also considered in this section as shown in Fig. 4(b). The fundamental ellipse is obtained through trials and errors, and is defined as

$$\frac{(a^*-\text{[illegible]})^2}{\text{[illegible]}^2}+\frac{(b^*-\text{[illegible]})^2}{\text{[illegible]}^2}=1 \quad (6)$$

and displayed in Fig. 5. In Fig. 4(a), the fundamental ellipse includes 99.91% of the collected rust colors. The fundamental ellipse shown in Fig. 4(b) defines 99.89% of the adjusted rust colors using illumination adjustment.

3.4 Application and discussion of the image preprocessing method

From section 3.1 to 3.3, automated detection of background defines the background color area, and the fundamental ellipse clarifies the rust colors. Fig. 5 shows the results of direct application of the image preprocessing, and Fig. 5(c) displays the scatter of color on the a*b* color plane. In a scatter, the darker, normal and lighter background colors constitute the region 1; the region 1 is defined by a box shape whose margins are decided by the extreme value of the background colors. Region 2 is composed of the color which is fallen in the fundamental ellipse. To a scatter, since only the color which falls in region 1 and 2 can be defined, the rest of colors are belonging to region3, called non-defined area. The Fig. 5(d) shows that the non-defined area contains the gradual change color form the mild-rust-color to background color. Therefore, the fuzzy concept is adopted to describe the mild-rust color.



(a) Original rust image

(b) Darker, normal, and lighter background color

(c) Scatter of pixels of the rust image on the a*b*plane and the fundamental ellipse

(d) Non-defined area (shown as region 3 in (c))

(e) The defined rust areas (shown as region 2 in (c))

Figure 5. Application of image preprocessing in non-uniformly illuminated rust image with blue paint

4. BOX-AND-ELLIPSE-BASED NEURO-FUZZY APPROACH (BENFA)

According to section 3.4, it shows that only the serious rust colors and the background colors are certain. The proposed model, BENFA, utilizes the fuzzy concept to deal with the non-defined area, adopts the neural network to decide the threshold of rust recognition by learning. Therefore, the adaptive-network-based fuzzy inference system (ANFIS) [10] is adopted to train the data.

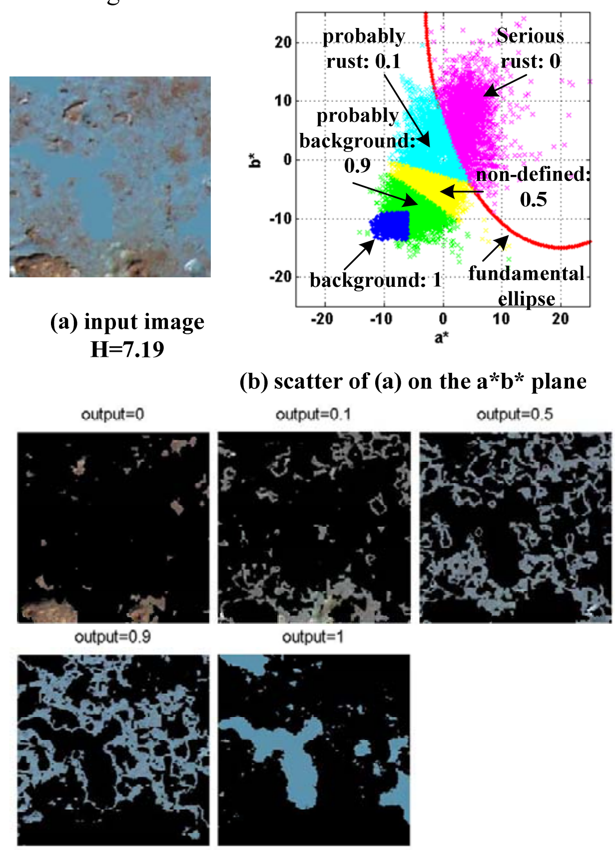
4.1 Input and Output of the BENFA

The first step is to decide the input of the ANFIS. The candidates of input include chrominance a*, chrominance b*, brightness L*, and the eigenvector of chrominance (a*, b*). Utilizing eigenvector aims to include the neighboring information. Through testing in several rust images, we find out that the L* may decrease the recognition results, and the eigenvector of (a*, b*) spends too much time in training. Therefore, only the chrominance a*, and b* are selected as the input.

The output of the rust colors and the background colors are designated as 0 and 1 respectively. Since it is too bulky to manually assign each input to its corresponding output, the automated input-output mapping is introduced in this section.

After applying the automated detection of background to about 500 rust images with size 256*256, we found out that the input should be classified into two groups by H=4, where H refers to entropy of an image. An image whose entropy higher than 4 means its colors are various and is suitable to apply the automated background detection. An image with low entropy means the color is simple, that is there is seldom chance to exist gradual change color between rust and background, so it is simply clustered into rust and background using the K-Means.

Entropy of chrominance higher than four represents the color variety is high, so it is meaningful to discriminate rust color into different intensities. Automated detection of background is applied to decide the area of background on the a*b* color plane; fundamental ellipse decides the serious rust color. To an input image, any data fall in the box area which is formed by automated detection of background method is background color and designated as 1; any data fall in the fundamental ellipse is serious rust color and designated as 0; the remaining data is clustered by the Fuzzy C-Means (FCM) [11] into three groups: probably rust, non-defined color, probably background, and they are designated as 0.1, 0.5, 0.9 respectively. Fig. 6 displays the designation result by RGB images.



(a) input image H=7.19

(b) scatter of (a) on the a*b* plane

(c) display the designation in RGB image

Figure 6. Designation of output with H >4

4.2 Illumination Adjustment

Since non-uniform illumination problem should always be considered in this paper, illumination adjustment is applied in the training stage of the BENFA. Theoretically, the recognition results of a rust image under different lighting conditions should be the same. Therefore, a uniform illuminated image is designated the input-output mapping as in section 4.1, and the mapping is stored. This image is then multiplied and divided by a constant to simulate different lighting conditions, and the corresponding output is assigned according to the mapping which is determined by the original image and stored before. Through testing in several rust images, we found out that each input image IM creates four more images with different brightness, that is IM*0.7, IM*0.9, IM*1.1, IM*1.3, would improve the recognition performance.

4.3 Automation of Rust Recognition

According to section 4.1 and 4.2, the BENFA could be constructed. The BENFA is composed of three sub-ANFIS which are divided by the chrominance b*, and each ANFIS are trained with generalized bell membership function. The chrominance a* and b* are assigned 4 and 6 membership functions respectively to build the fuzzy inference system. Fig. 7 shows the output of the BENFA, where the input is a 256*256 rust image.

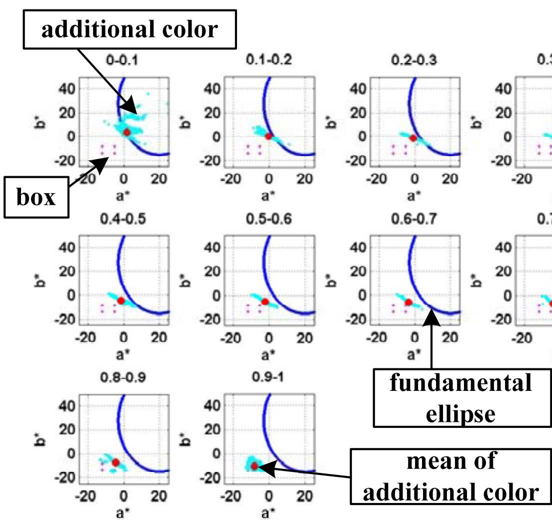


Figure 7. Output of the BENFA

Fig. 7 shows that the additional colors gradually move and change from the serious rust color to the background, so the two thresholds of serious rust and mild rust are determined by the mean of the additional colors. From 0 to 1, once the mean falls out of the fundamental ellipse (ex. 0.1-0.2), the additional colors are further divided into four parts (ex. 0.1-0.125, 0.125-0.15, 0.15-0.175, 0.175-0.2). Then the biggest range whose mean of the additional colors does not fall out of the fundamental ellipse is chosen, and its maximum value is selected to be the threshold of the serious rust (THs). Similarly, the threshold of the mild rust is determined in this way. Once the mean falls in the box area which is determined by the extrema of the automated detected background, the additional colors are divided into four. Then the biggest range whose mean of the additional colors does not fall in the box is chosen, and its maximum value is selected to be the threshold of the mild rust (THm). Fig. 8 displays the flowchart of the BENFA.

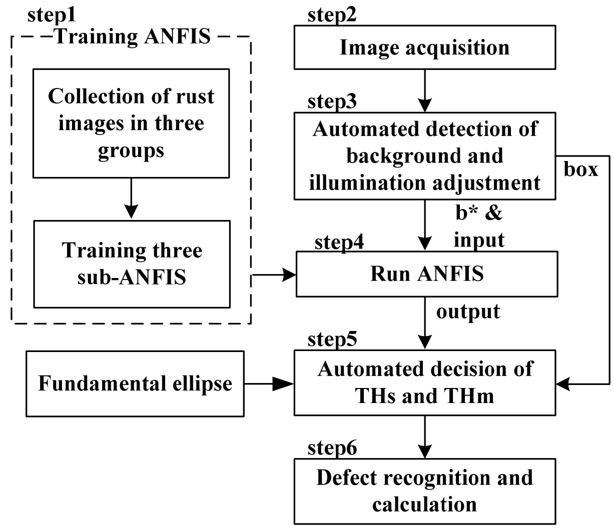


Figure 8. Flowchart of the BENFA

5. RESULTS AND COMPARISIONS

The rust recognition results of the proposed box-and-ellipse-based neuro-fuzzy approach (BENFA) are compared with the Fuzzy C-Means (FCM). The FCM is based on the K-Means algorithm, and the fuzzy concept is applied in the clustering algorithm. Since it is often used in the literature [4], the FCM is selected as the benchmark to the proposed BENFA. Fig. 9 shows that the BENFA could recognize the rust intensity in terms of the mild rust percentage area and serious rust percentage area, while the FCM just clustered the data into three groups. Fig. 10 shows the stability of the BENFA. When there is no distinct groups on the a*b* color plane, the FCM could not cluster the data well; the BENFA has its own consistent standard to segment a rust image.

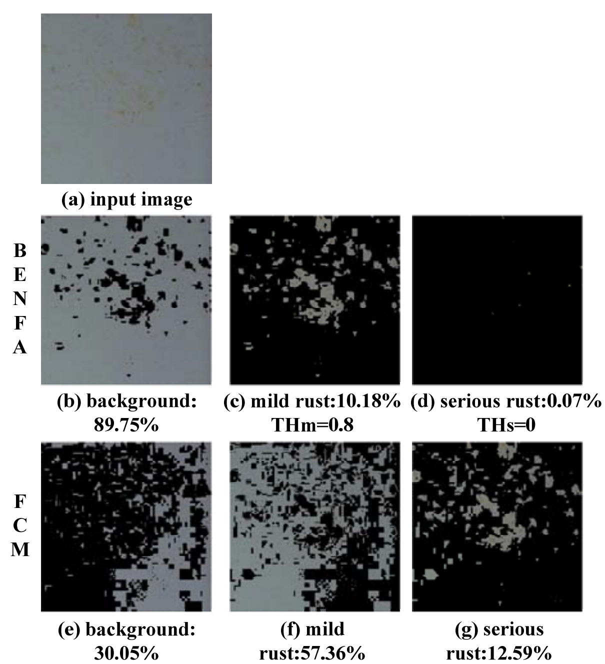


Figure 9. Rust intensity recognition of the BENFA

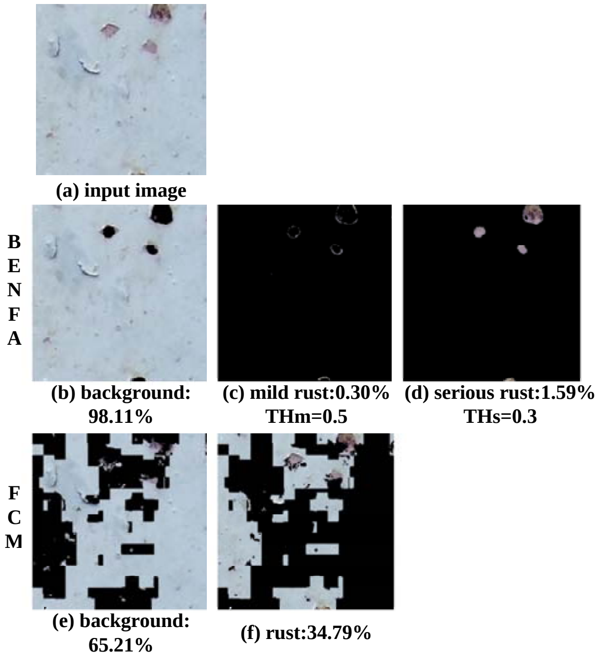


Figure 10. Stability of recognition of the BENFA

6. CONCLUSIONS

This paper adopts the color image processing in rust recognition. Through testing in 50 rust images in 14 color spaces, the a*b* color configuration is considered as the best color plane for light filtering. The proposed BENFA is developed in the a*b* color configuration.

Through the observation of several rust images, it is found out that the rust colors are more complicated than the background colors. This fact triggers that the image preprocessing starts with background elimination. The proposed image preprocessing includes the automated detection of background, illumination adjustment, and fundamental ellipse which is used to defined the serious rust colors. The colors which could not be defined in image preprocessing step are non-defined colors. The non-defined colors include the gradual change colors from mild-rust to background. Therefore, the fuzzy concept is adopted to describe the non-defined area.

The proposed box-and-ellipse-based neuro-fuzzy approach (BENFA) is trained by the adaptive-network-based fuzzy inference system (ANFIS) with 120 rust images with size 256*256. The BENFA includes the illumination adjustment which aims to overcome the non-uniform illumination problem. The rust intensity could be automatically recognized by the BENFA. Compared with the Fuzzy C-Means (FCM), the BENFA could recognize the rust intensity in terms of mild rust and serious rust percentage area. Also, the BENFA has better stability of recognition than the FCM. It has to be acknowledge that the BENFA could not deal with the rust images with brown coating. Since the BNEFA applied the automated detection of background, the coating could not be similar to the rust color. However, it would not be a big problem, as usually paints with colors distinct from rust colors will be chosen for steel bridge coating.

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