**S8-1**

# ADAPTABLE ELLIPSE METHOD FOR BRIDGE COATING DEFECT RECOGNITION

**Po-Han Chen[1], Ya-Ching Yang[2], and Luh-Maan Chang[3]**

[1] Assistant Professor, School of Civil and Environmental Engineering, Nanyang Technological University, Singapore
[2] Student under Dual Master Degrees, Nanyang Technological University, Singapore and National Taiwan University, Taipei, Taiwan
[3] Professor, Dept. of Civil Engineering, National Taiwan University, Taipei, Taiwan
Correspond to CPHChen@ntu.edu.sg

**ABSTRACT:** Image processing has been applied to steel bridge defect recognition since 1990s. Compare to human visual inspection, image processing provides a more objective and accurate way of assessment. Since shade and shadow may sometimes occur when taking bridge coating images, non-uniform illumination problems should be considered. By means of color image processing, this paper aims to mitigate the illumination effect for bridge coating assessment. Furthermore, the adaptable ellipse method (AEM) is proposed to recognize mild rust colors. Finally, AEM will be compared to the K-Means algorithm, a popular recognition method, to show its advantage.

*Keywords: Color image processing; rust defect recognition; non-uniform illumination; colo*

*r configuration; K-Means*

# 1. INTRODUCTION

Traditional steel bridge defect assessment is carried out by engineer's visual inspection which is time and cost wasting and lack of consistency. 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.

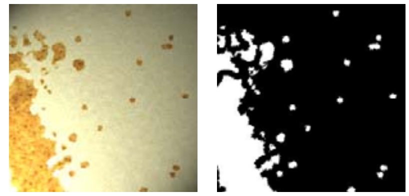
In previous studies, most of the models process in grayscale image which could not deal with non-uniform illuminated images well [1-3]. Although Lee (2005) proposed a model by color image processing, its threshold should be determined in advanced. Therefore, this paper aims to solve non-uniform illumination problem by means of color image processing. The first step is to select the best color coordinate system from 14 existing color spaces. Also, the proposed adaptable ellipse method (AEM) would automatically determine a threshold for rust (include the mild-rust-color) recognition. Finally, the recognition results of AEM will be compared with the clustering results of the K-Means.

# 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 [4]. 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* [4-6].

## 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:

5. Randomly select K data points as the initial cluster means (or cluster centers);
6. 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;
7. Re-calculate the mean of each cluster (and set it as the new cluster center);
8. 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. 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.

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

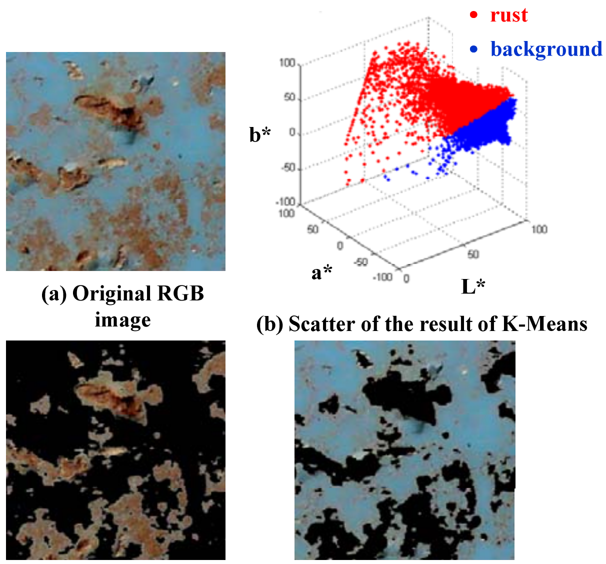
$$a^* = 500\left[f\left(\frac{X}{X0}\right) - f\left(\frac{Y}{Y0}\right)\right] \tag{2}$$

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

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

## 3. WHY NOT K-MEANS

Although the K-Means algorithm is considered as one of the simplest and most promising methods in prior research, the algorithm in nature is hard to interpret the gradual change area between the rust and the background.




(a) Original RGB image

(b) Scatter of the result of K-Means

(c) Rust

(c) Background

Figure2. Segmentation results of K-Means

Fig. 2 shows the segmentation results using the K-Means. Fig. 2(b) presents that there are no prominent groups to a rust image. Due to this nature of rust image, it is hard to deal with the mild-rust-color well. Fig. 2(c) shows that the mild-rust-color is misrecognized as the background color. Therefore, the proposed adaptable ellipse method (AEM) will aim to achieve the mild-rust recognition.

## 4. IMAGE PREPROCESSING

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

### 4.1 Automated Detection of Background

According to Fig. 2(b), the rust colors vary in the color space, 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:

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

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

8. 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.

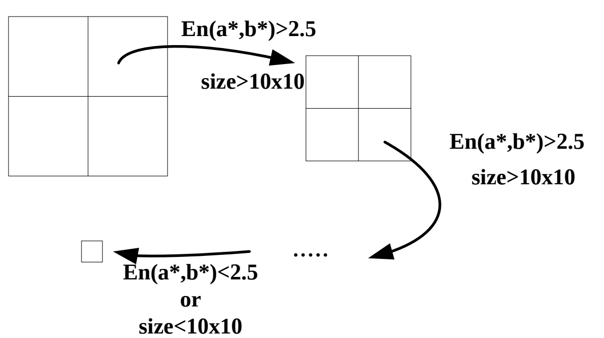



Figure3. Process of automated detection of background

Fig. 3 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.

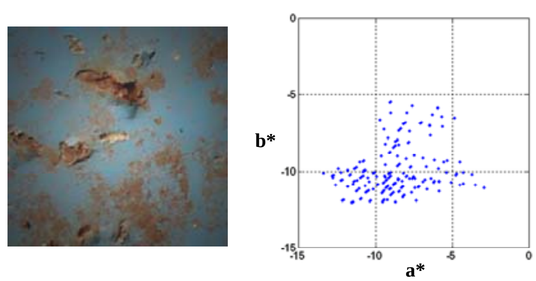
### 8.2 Illumination Adjustment

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.

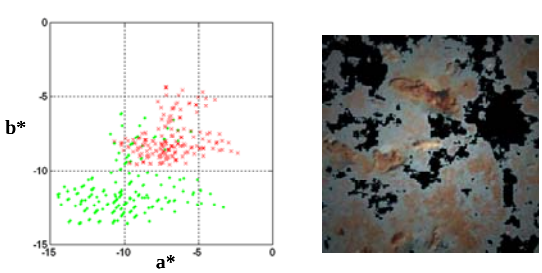
Illumination adjustment is processed in the RGB color space and is used to adjust the light intensity (or illumination) of rust images so that the light effect on background colors could be better studied and handled. In the RGB color space, a color will remain the same after multiplying or dividing the three components (R/G/B) by a constant[7]. 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[7]. 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. Finally, the background areas on the rust image could be approximated using the background color definition on the a*b* plane. Fig. 4 shows the elimination result of background colors.




**(a) Non-uniformly illuminated rust image** **(b) Automated background detection on the a*b* plane from (a)**

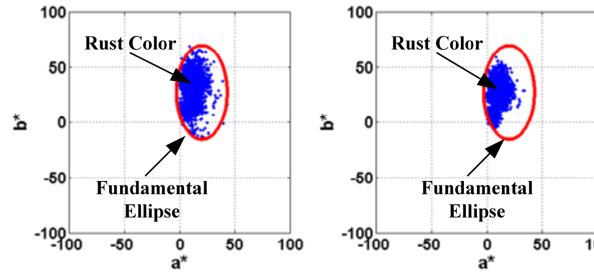



**(c) Illumination adjustment from (b)** **(d) Elimination of background**

Figure 4. Result of background elimination after illumination adjustment

### 4.3 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 5. Rust colors and the fundamental ellipse

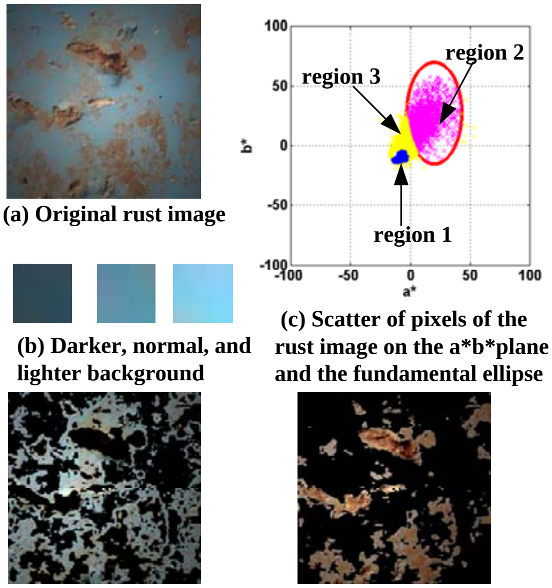
The scatter of the rust color in Fig. 5 looks like an ellipse. In 2000 Adachi et al. proposed to use an ellipse to approximate the flesh color on the UV plane, which is one of the color configurations of the LUV color space, for face detection [8]. The previous work motivates this paper to approximate 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. 5. The fundamental ellipse is defined according to all the collected rust colors, as shown in Fig. 5(a). Since non-uniform illumination is always an important issue, illumination adjustment is also considered in this section as shown in Fig. 5(b). The fundamental ellipse is obtained through trials and errors, and is defined as

$$\frac{(a^*-20)^2}{23^2}+\frac{(b^*-27.8)^2}{45.8^2}=1 \tag{6}$$

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

## 5. ADAPTABLE ELLIPSE METHOD (AEM)

The proposed adaptable ellipse method (AEM) is composed of the three parts of image preprocessing, automated detection of background, illumination adjustment, and the fundamental ellipse. Fig. 6 displays the results that directly apply the image preprocessing on a rust image.




**(a) Original rust image**

**(b) Darker, normal, and lighter background**

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

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

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

Figure 6. Application of image preprocessing in non-uniformly illuminated rust image

In a scatter as shown in Fig. 6(c), 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.

Although the fundamental ellipse defines the serious rust color, the mild rust colors are still not included. In Fig. 6(d) the points designated by region 3 are the non-defined area which contains both mild rust color and background color. The AEM is focus on the treatment of the non-defined area by means of adjusting the size of the fundamental ellipse.

From the comparison of different images with several paint colors, we can find out that the relative relationship between the serious rust color defined by the fundamental ellipse and the background color depends on the paint color. Therefore, each steel bridge should have its own ellipse to segment the rust area. The AEM is determined by the steps:

1. After automatically define the background color, there are three groups, background, rust (enclosed by the fundamental ellipse), and the non-defined color.
2. A line is linked by the means of the rust group and the background group, and its intersect with the fundamental ellipse is a new point, called i1, for enlarging the fundamental ellipse (see Fig. 7).

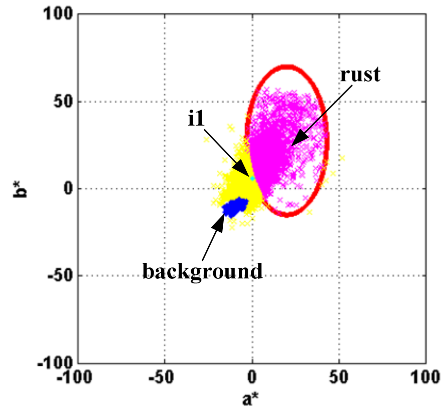



Figure 7. Enlargement size is based on the distance between i1 and the mean of background color

The enlargement percentage of the fundamental ellipse depends on the distance between i1 and the center of background. Also, the new area of ellipse should not include the background color.

In order to induce the enlargement percentage of the fundamental ellipse, 11 real rust images are processed by the previous three steps. According to the experiment, we find out that the optimal enlargement percentages always fall under 50% where is the middle area of the gradual change between rust and background color. Most of the optimal percentages are the second largest success percentage where 50% is the upper limit. Therefore, the enlargement percentage of the AEA is determined by the second largest success percentage and 50% is always set to be the upper limit.

Each steel bridge has to run the AEM to produce its own ellipse. Deriving a new ellipse for each steel bridge from a 256*256 rust image spends about 40 seconds. Then this ellipse can be used to segment the rust area in the same bridge very fast. Fig. 8 shows the flowchart of the AEM.

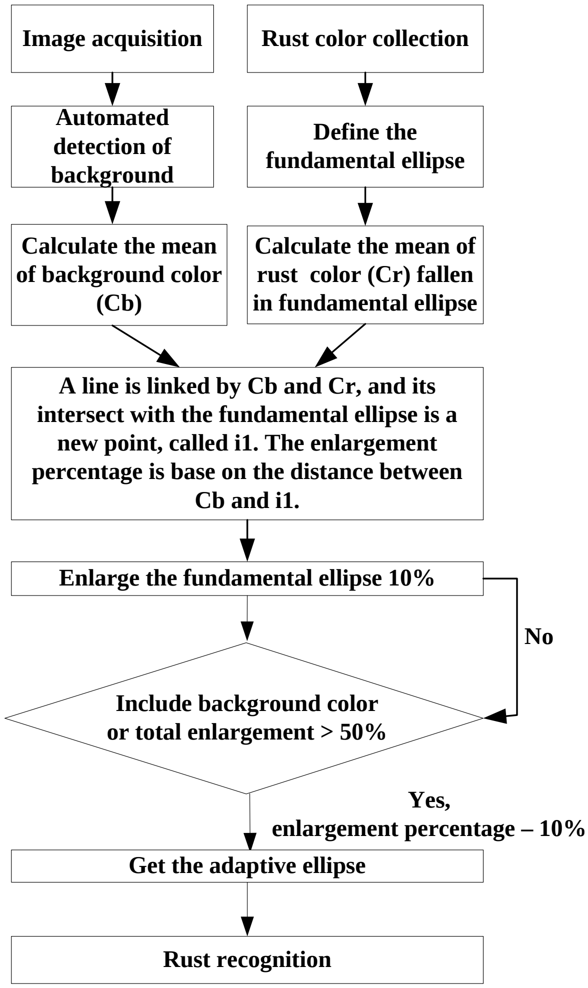



Figure 8. Flowchart of the AEM

## 6. RESULTS AND COMPARISONS

### 6.1 Comparison of K-Means in grayscale, RGB, and a*b*

In section 2, the a*b* configuration (of the L*a*b* color space) is found to be the best color coordinate system. Fig. 9 and Table 2 shows the clustering results of a non-uniformly illuminated image sample using the K-Means algorithm under grayscale, RGB, and a*b*, respectively. Note that all the results are shown in RGB format. Fig. 9 shows that only the a*b* configuration is independent of illumination, which implies that a*b* has moderate ability to filter illumination/light factors. In summary, the a*b* configuration is found to have the best performance in clustering steel bridge rust images in this paper. Also, all of the results show that the mild rust colors are more likely to be recognized as the background color using the K-Means algorithm.

Table 2. Processing time for a 256x256 rust image using the K-Means algorithm

| Time (sec) | Grayscale | RGB | a*b* |
|---|---|---|---|
| Average | 8.09 | 11.01 | 23.23 |

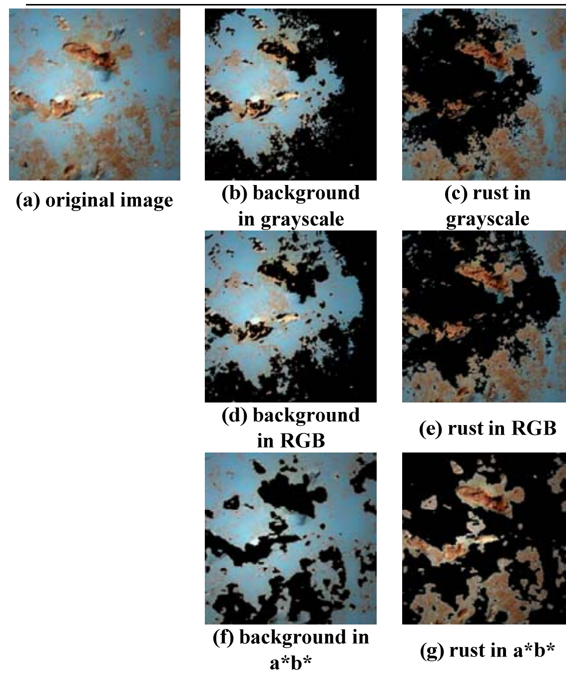



Figure 9. Comparison of the processed results of a non-uniformly illuminated image using the K-Means algorithm

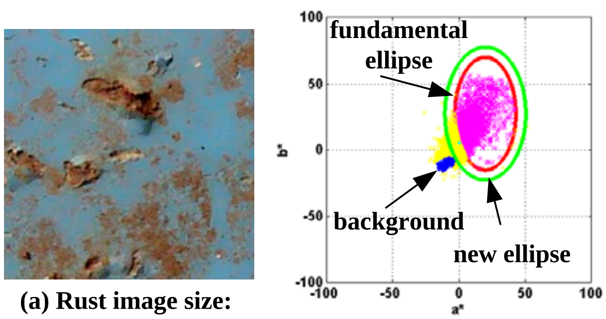
### 6.2 Comparison of K-Means with AEM

Considering that the K-Means is one of the most effective segmentation method in the literature [3], it is chosen to be the benchmark for the proposed adaptable ellipse method (AEM). The segmentation results of a 256*256 image by K-Means are shown in Fig. 10. It can be seen that most of the mild-rust-colors are regarded as the background color in Fig. 10(b). This fact decreases the rust area percentage to only 30%, as shown in Fig. 10(c). This is the disadvantage of the K-Means due to its algorithm. A data without distinct groups could not be clustered well. Generally, the K-Means algorithm can generate good results if the groups of data to be classified are distinct. Since the non-defined colors in this case have vague boundaries with background colors and with rust colors, the segmentation results might be unsatisfactory sometimes. Therefore, a more reliable approach for rust image recognition is required. This is why the adaptable ellipse method (AEM) is proposed in this paper.

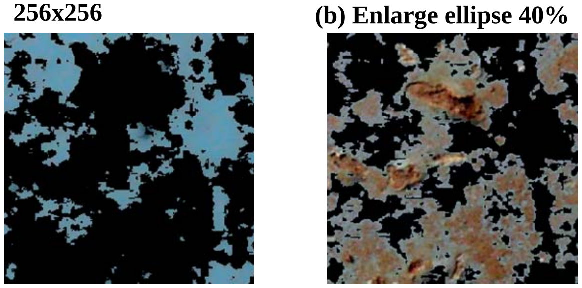
**(a) Rust image size: 256x256** **(b) Background** **(c) Rust percentage: 30%, processing time: 25sec**

Figure 10. Processed results using the K-Means algorithm

Fig. 11 displays the segmentation result of the rust image in Fig. 10 using the adaptable ellipse method (AEM). The color relationship on the a*b* plane is presents in Fig. 11(b). The new ellipse which is enlarged from the fundamental ellipse includes most of the mild-rust-color. Fig. 11(d) shows the rust recognition which is constructed by the pixels whose color falls in the new ellipse. Compared to Fig. 10(c), Fig. 11(d) includes the mild rust areas and increases the rust percentage to 65%. The processing time required by AEM is acceptable, as shown in Table 3.




**(a) Rust image size: 256x256** **(b) Enlarge ellipse 40%**



**(c) Automated detection of background** **(d) Rust percentage: 65%, processing time: 33 sec**

Figure 11. Processed results using the adaptive ellipse approach (AEA)

Table 3. Processing times for a 256x256 rust image on the a*b* color plane

| Time (sec) | K-Means | AEA |
|---|---|---|
| average | 23.14 | 32.32 |

Although AEM has been proved effective for rust image recognition, there is still a limitation. Since AEM is developed based on color/chrominance similarity on the a*b* plane, any color close to brown is considered as rust in this approach. Therefore, if the paint color of steel bridge coating is similar to brown or red colors (i.e., rust colors), the recognition accuracy of AEM will go down. However, it is not a big issue, as in most cases people would choose a paint color distinct from rust colors (or brown/red colors) for steel bridge coating.

## 7. CONCLUSIONS

With the prevalence of computerized technologies, color image processing becomes possible in applying in automated infrastructure assessment. Through processing 50 uniformly and non-uniformly illuminated rust images using the K-Means algorithm, it is found that the a*b* configuration (of the L*a*b* color space) has the best performance in rust image recognition due to their ability in filtering out light effects (or illumination factors). Therefore, the a*b* color configuration is adopted in this paper.

Based on the observation that background colors are much easier to deal with than rust colors, which have a wider coverage of tones and shades of brown (or rust) colors (from serious rust colors to mild rust colors), the adaptable ellipse method (AEM) is developed. The fundamental concept is to classify the rust image into three groups: background colors, rust colors, and non-defined colors (may include background color or mild-rust color). The approach is designed for automatic rust recognition and rust percentage calculation. In AEM, background colors and rust colors defined by the fundamental ellipse could be easily identified, but it takes some effort to process non-defined colors. To classify non-defined colors, a new ellipse, which is enlarged from the fundamental ellipse, is used.

Through experiments, it is proved that the proposed adaptable ellipse method (AEM) has excellent ability for rust image recognition and could identify a wide range of rust colors. On the contrary, the performance of the popular K-Means algorithm is not as good as that of AEM due to the lack of ability to handle light/illumination factors. Despite all the advantages, AEM has one shortcoming, not being able to properly recognize rust images of brown or red paint colors. 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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