Detection of Corrosion Defects in Steel Bridges by Machine Vision

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Abstract. Existing bridges are critical components of transportation infrastructure manly due to a huge volume of different corrosion. Corrosion reduced the performances of bridges and decrease their life services. Towards automatic detection of corrosion defects during inspections, a novel methodology is here proposed making use of machine vision concepts. Indeed, different types of corrosion can be detected by image processing techniques that can be an appropriate tool also for the prediction of the damage evolution in bridges. Clustering K-means algorithms on image segmentation have been used to classify corrosion defect levels.

Keywords: Image processing · Clustering K-mean algorithm · Defect detection · Corrosion · Automatic inspection

1 Introduction

Steel bridges are widely used in the transportation infrastructures due to economic production, speed and versatility in construction. The corrosion process propagates on the external surface due to the weather condition and material property of the structural elements. The material degradation causes the corrosion in presence of specific environmental conditions [1]. According to appearance the corrosion is categorized as, pitting type, general (uniform), fatigue atmospheric corrosion [2, 3]. NACE declared the pitting defect type is more dangerous than uniform corrosion due to the difficulty in detection [4]. Sometimes the corrosion may lead to cracking which is known as Stress Corrosion Cracking. Therefore, correct evaluation of the structure is necessary to prevent the catastrophic fracture of the bridges and put the environment and human in danger. There are different types of non-destructive testing for corrosion detection which all of them have their limitation for instance the range of inspection is limited or the efficiency of defect identification [5].

Robotized inspections may overcome the time-consuming expensive problem of the traditional method that the defects are measured visually by the operators [6–8]. In this area, research needs of defect detection by machine vision. This paper focus on image processing technique for detecting defect ranges from input image. The image processing has been utilized for corrosion defect detection of the Quisi railway steel truss bridge.

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The accuracy of defects detection in the steel bridge is improved with respect to digital image recognition using RGB technique [7, 9] comparing the achievable results with the ones obtained by segmentation in edge detection and K-means clustering.

2 Acquisition of Images in a Real Case Study

The case study is related to the Quisi Bridge an historic steel truss railway bridge, located in Benissa (Alicante), which is investigated with different techniques to assess the presence of fatigue damages see Fig. 1. The structure is categorized as a top bearing Pratt type truss with the length of the 170 m in a variety of six spans. It was built in 1914 and it is part of the 9th FGV Railway Line. The properties of materials used for its construction are reported in Table 1. The images have been acquired using UAV performing automatic inspection [7, 10].

Fig. 1. Quisi (railway) steel truss bridge-Benissa

Table 1. Material properties of steel for the Quisi bridge

Type of material	Old name	Tensile strength [Mpa]	Standard
S355	ST-52	470–630	DIN EN 10025-2

3 Unsupervised K-Means Clustering

The K-means clustering method is an unsupervised method that tries to label the input data based on the similarities and dissimilarities. In this method, K is the cluster number and each cluster is recognized based on the similarities and by defining the minimum distance to the center of each cluster by the higher similarities [12]. In this research, Euclidean distance is used for clustering of the images RGB. First, it could be good to introduce one of the key-value for the image processing process which is called RGB.

RGB return to a model that describes colors based on the intensity of red, green, and blue by the acronym of RGB on a scale of 0 to 255 [9], where can explain by:

$$\{\overline{R}_{ij}, \overline{G}_{ij}, \overline{B}_{ij}\}_{nxn} = \frac{1}{N}\sum\nolimits_{K=1}^{N}\{\overline{R}_{ij}, \overline{G}_{ij}, \overline{B}_{ij}\}_{nxm}\{\sigma_{Rij}, \sigma_{Gij}, \sigma_{Bij}\}_{mxn}$$

$$= \sqrt{\frac{1}{N}\sum\nolimits_{K=1}^{N}[\{\overline{R}_{ij}, \overline{G}_{ij}, \overline{B}_{ij}\}_{nxm}\{\sigma_{Rij}, \sigma_{Gij}, \sigma_{Bij}\}_{mxn}]^2}$$

where $\{\overline{R}_{ij}, \overline{G}_{ij}, \overline{B}_{ij}\}_{nxn}$ denote the matrix formed by the mean of each pixel of red, green and blue channels of the background. $\{\overline{R}_{ij}, \overline{G}_{ij}, \overline{B}_{ij}\}_{nxn}$ is the red, green and blue and by the standard deviations of the red, green and blue intensities for every pixel $\{\sigma_{Rij}, \sigma_{Gij}, \sigma_{Bij}\}_{mxn}$ formed as a matrix.

One of the most important keys in the machine vision is to evaluate the environment of the system to get a better vision of the structure. Therefore, the color of the surface for different level and kinds of the defect in the bridge may be a good parameter for investigation of the structures. The first two images captured for further defect analysis from the Quisi steel truss bridge are shown in Fig. 2.

Fig. 2. Two different images from Quisi railway steel bridge

In this study, the K-means clustering method is used. K-means clustering method can detect different types of defects in the images of the portion of the structure in which corrosion appears. For this aim, Matlab R2021a have been used and the step of K-Means evaluation have been considered following the flow-chart reported in Fig. 3.

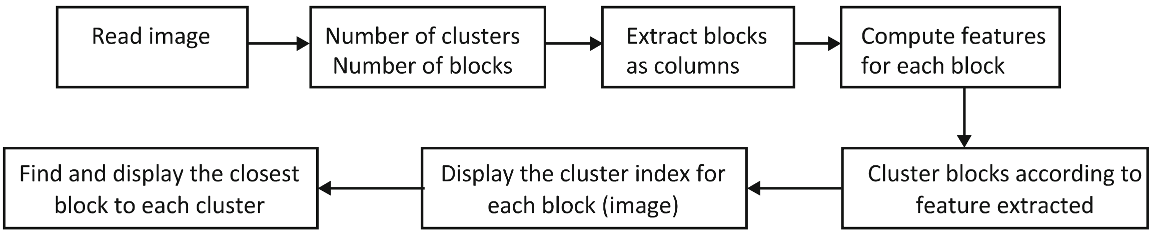
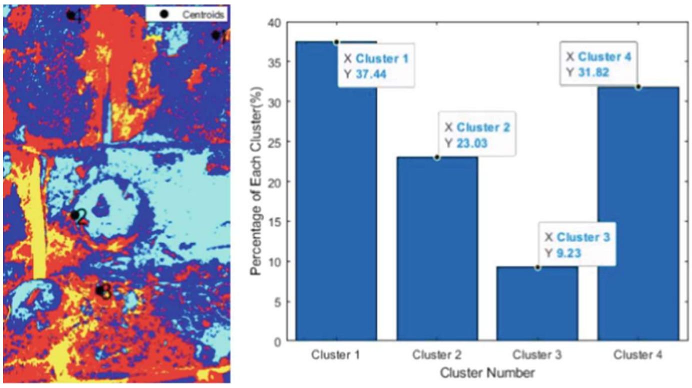


Fig. 3. Sequences for corrosion detection and quantification process.

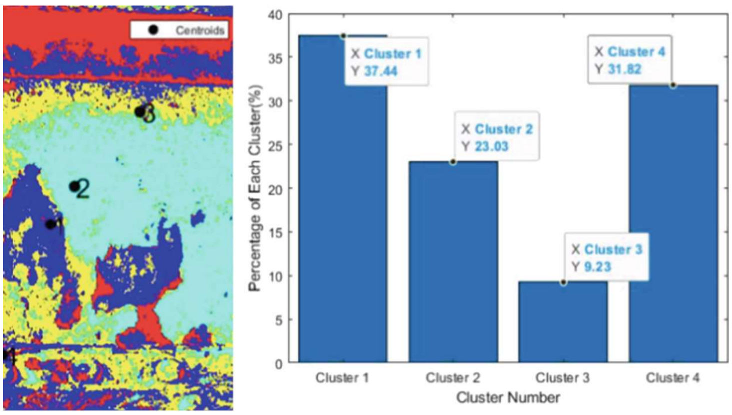
Based on the outcomes from the K-means four different clusters are obtained which are shown for image 1 in Fig. 4a and each cluster center shows by corresponding number

1 to 4. The Center of each cluster is Additionally, the level of each cluster corresponding with each defect is considered by the bar diagram in Fig. 4b. In the next step, the considering sequence of K-means applied for the second image as illustrated in Fig. 5a and the refereeing percentages of each cluster bring in Fig. 5b.



(a) Clustering center in each defect detection based on image 1
(b) Percentage of each cluster according to each individual defect

Fig. 4. Image processing–based on image 1



(a) Clustering center in each defect detection based on image 2
(b) Percentage of each cluster according to each individual defect

Fig. 5. Image processing–based on image 2

4 Conclusions

In this study, machine vision image processing was used to identify the presence of different defects in the same image by K-means clustering algorithms. The experienced feature of the proposed technique appears appropriate for corrosion defect detection. The results showed the high ability of K-means to describes the corrosion and their percentages. Through the proposed method the efficacy of automated inspection is enhanced for the structural health monitoring of the Quisi steel bridge. K-means clustering algorithm is experienced as an appropriate technique for defect detection.

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