Automation in Construction 90 (2018) 178–187

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Human-visual-perception-like intensity recognition for color rust images based on artificial neural network

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ARTICLE INFO

Keywords:
Rust
Visual perception
K-means
Artificial neural network
Root-mean-square standard deviation (RMSSTD)

ABSTRACT

Digital image processing has been applied to the assessment of steel bridge coating quality since the late 1990s. Most previously developed methods cluster rust images into two or three groups before calculating the rust percentage. Since two- or three-group clustering might not properly reflect the rust intensity or rusting severity on a rust image, the artificial-neural-network-based rust intensity recognition approach (ANNRI) is proposed in this paper.

ANNRI integrates the root-mean-square standard deviation (RMSSTD) and artificial neural network (ANN) to cluster a rust image based on its rust intensity or rusting severity. RMSSTD measures the similarity of rust colors on a rust image, and an ANN trained with the results of a human visual rust inspection experiment would generate the optimal number of clusters for rust intensity recognition. Together with a pre-defined rust color spectrum, ANNRI is able to perform human-visual-perception-like rust intensity recognition and screen out background noises. According to the experiments conducted in this study, the proposed ANNRI can discriminate rust intensity much better than the existing methods with a fixed number of clusters.

1. Introduction

Bridges are very important infrastructure facilities in a country. In Taiwan, an island full of mountains and rivers, the government has to build new bridges and maintain more than 13,000 existing bridges [33]. Among the various bridge types, steel bridges are popular due to their relatively light weight, ease of construction, and short building period [28,45].

However, unexpected collapses of infrastructure facilities have been reported worldwide due to overuse and/or aging of the facilities. For example, the I-35W Mississippi River Bridge, a steel truss arch bridge across the Mississippi River in Minneapolis, Minnesota, U.S.A., collapsed on August 1, 2007, resulting in a devastating loss of human lives and properties. In order to ensure the safety of a steel bridge, the bridge condition should be monitored and assessed in regular inspections, and surface coating quality is an important indicator for the condition of a steel bridge.

A traditional method to describe the health condition of a steel structure is the ratio of the rust area to the total coated area. The American Society for Testing and Materials (ASTM) classified coating defects into ten degrees according to the defect percentage. For each degree of coating defects, it provides suggestions on how to rectify the defects [2]. However, it is hard to decide the rust percentages with human eyes in an objective manner. This is a common problem faced by many departments of transportation in the U.S.A. The visual inspections are relatively subjective, inconsistent, and time-consuming [41]. Tam and Stiemer [42] have stated that visual quantification of the defect percentage could be very difficult even for well-trained inspectors. Hence, digital image processing was brought into this domain to help assess rust images and generate objective results.

In North America, image processing for steel bridge coating inspection has been used since the late 1990s [1,10–14,30,48]. Compared to visual inspection, using digital image recognition to process steel bridge coating images is efficient, consistent, accurate, and objective. There are a number of image segmentation methods in computer vision and image processing applications for the extraction of interested objects on an image [17,18,25,26]. The segmentation methods can be classified into the following categories: edge-based, threshold-based, region-based, neural-network-based, cluster-based, and hybrid. Despite the wide applications of computer vision methods, few of them were tailored for rust image recognition. As digital image processing is in need of extensive experiments to solve a given problem [20], most methods were developed to solve problems in a specific domain. In order to apply image processing to steel bridge coating inspection applications, researchers have been devoted to feature selection and feature data acquisition of steel bridge coating, and evaluating the

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https://doi.org/10.1016/j.autcon.2018.02.023
Received 31 December 2015; Received in revised form 23 January 2018; Accepted 8 February 2018
0926-5805/

feasibility of proposed methods.

In 1999, AbdelRazig proposed a hybrid model (NNHM) which integrated artificial neural networks (ANNs) for the defect recognition of steel bridge painting [1]. The hybrid model clusters a grayscale image into two groups, rust and background, using the K-Means algorithm. A threshold value, obtained from the clustering result of K-Means, is set as the target value for the ANN, and the gray level of each pixel and its deviation from the threshold are the input to the ANN. By means of the training process, a well-trained ANN could simulate experts' knowledge to assess the rust degree of a steel bridge automatically.

Chen and Chang [14] proposed a neuro-fuzzy recognition approach (NFRA), which integrated artificial neural networks and fuzzy adjustment, to process steel bridge coating images in 2002. NFRA divides a grayscale image into different areas in accordance with the illumination of the pixels. Each area has its threshold value which is generated by the trained ANN. Moreover, fuzzy logic is applied to adjust the illumination values along the boundaries of different areas. Due to the limited computer performance around the year 2000, images were converted to grayscale before further processing. The performance of NFRA was slightly better than other image processing methods developed earlier at the time.

In order to overcome the problems caused by particular environment conditions, Lee [29] established a complete steel bridge surface assessment method using color images. The method maps steel bridge coating images to the Cb/Cr color configuration of the YCbCr color space, and then projects all the data on a horizontal axis through the Hotelling transform to separate rust from background. This method worked effectively with blue coating images taken in the State of Indiana, U.S.A.

Yang and Chen proposed an adaptive ellipse approach (AEA) to classify rust images into three groups, background colors, rust colors, and non-defined colors (such as mild rust colors, etc.), to describe the surface coating condition of steel bridges [11,48]. In AEA, background colors and rust colors are recognized using the fundamental ellipse which was defined by the widely collected rust colors. The AEA enlarges the fundamental ellipse to include part of the gradual changes in colors, and the enlarged size depends on the relationship between the rust colors and the coating color. This method deals with the boundary between the background color and the rust colors, and improves the accuracy of rust percentage due to the minimization of classifying light rust colors into background.

Similar to the disadvantage of two-cluster rust image segmentation (Fig. 1), AEA, which has a fixed number of three clusters, may not be the best way to describe gradual rust color changes in rust intensity recognition. Thus, a method that can identify the optimal cluster number and describe rust intensity is needed, since rust intensity could indicate the severity of rusting and provide rust percentages with a better accuracy. These pieces of information would be of great help to the bridge authority in the allocation of bridge maintenance budgets.

In order to obtain the optimal number of clusters (i.e., color groups, inclusive of background and rust color groups), a clustering analysis is used [8]. An image is first divided into a number of clusters, and the root-mean-square standard deviation (RMSSTD), which is an indicator of cluster variances (Eq. (1)), is calculated [21,24,36,37,47]. The RMSSTD measures the homogeneity of clusters to identify homogenous groups. A smaller RMSSTD value indicates a higher level of homogeneity within the group. If the largest difference of the RMSSTD values is between cluster n-1 and cluster n, n will be the optimal number of clusters.

$$RMSSTD = \sqrt{\frac{\sum_{\substack{i=1..n_c \\ j=1..d}} \sum_{k=1}^{n_{ij}} (x_k - \bar{x}_j)^2}{\sum_{\substack{i=1..n_c \\ j=1..d}} (n_{ij} - 1)}} \tag{1}$$

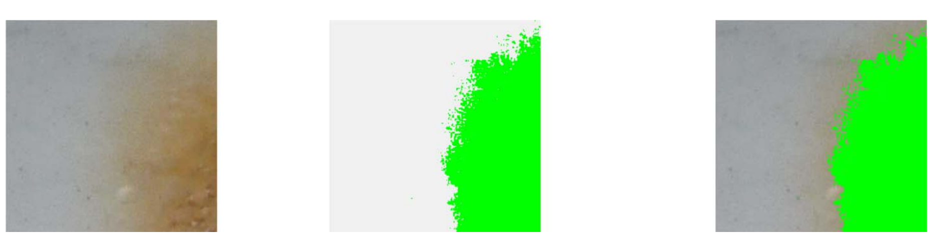
where n_c is number of cluster, d is number of dimension$\bar{x}_j$ is expected value in the jth dimension.n_{ij} is number of element in ith cluster jth dimension.

Theoretically, this method should be more ideal than the previously developed two- or three-cluster methods, since this method could automatically determine the optimal cluster number without the need of specifying it. However, when applying it to steel bridge coating assessment, its performance is not as good as expected and it always classifies rust images into two clusters owing to the significant difference between the rust and the background. In this regard, the artificial-neural-network-based rust intensity recognition approach (ANNRI) is proposed in this paper for the automatic selection of the optimal cluster number (which could be used to infer the severity of rusting) based on the RMSSTD values.

2. Rust intensity recognition using RMSSTD

The number of clusters is an important factor to describe rust intensity, i.e., severe rust, mild rust, and light rust. In practice, a human inspector would discriminate rust based on the relatively differentiable rust colors, which are positively related to the rust color clusters obtained in digital image processing. The more the rust color clusters, the more the details of gradual rust color changes. However, how many clusters best describe the rust intensity situation of a rust image is somewhat subjective. Fig. 2(b) to (f) shows the segmentation results of Fig. 2(a) when the number of clusters changes from two to six. Since different people might have different perception on the optimal number of clusters in rust image segmentation, a survey was designed and conducted.

In the survey, 35 steel bridge rust images of 256-by-256 pixels were used (Fig. 3) and 41 civil engineers participated in the survey. The rust images were taken at a fixed distance (30 cm) from the surface of steel bridges in Taiwan, under the non-illumination condition. The real bridge coating pictures were taken from Dazhi Bridge, Huandong Boulevard Rainbow Bridge, Guandu Bridge, and so on in 2008. 63% of the survey participants were from construction companies and 37% from consulting companies. Among them, 13 (32%) had less than 5 years of working experience, 11 (27%) had 6–10 years of experience, 9 (22%) had 11–15 years of experience, and 8 (19%) had more than 16 years of experience. During the survey, each participant was given



(a) Original image, with a size of 256 x 256 pixels (b) Two-cluster segmentation result (c) Some light rust colors are classified into background

Fig. 1. Two-cluster rust image segmentation.