Automated Detection of Corrosion Damage in Power Transmission Lattice Towers Using Image Processing

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Abstract

Corrosion is a serious issue causing damage in power transmission lattice towers of steel that can lead to outages. In spite of initial galvanization, periodic repainting and usage of weathering steels, corrosion is experienced in lattice structures at locations with constant exposure to moisture and inaccessibility to repaint. In the present day there are a huge number of transmission towers built of carbon and weathering steels with corrosion posing serious threats to their bearing capacity and durability. Timely inspection and repair is essential to avoid unprecedented structural failures. Employing non-destructive methods of manual inspection for large number of towers to detect corrosion and related damages is time consuming and expensive. In addition to this, the drawbacks include error due to inaccurate human judgment questionable safety of inspector to climb structures possibly weakened by corrosion. In such a situation non-contact approach of automated visual inspection for corrosion and related damage detection through image processing of aerial or ground based images is a viable option. A combination unsupervised and supervised classification methods is used to identify corroded regions in power transmission tower images using various color features of the image. The image is segmented into clusters based on the colors in L*a*b* color space using K-means clustering algorithm. These segments are tested against the conditions of hue obtained from statistical analysis of hue values corresponding to a set images of corroded surfaces to identify the segment of the image with corrosion. This approach lays a foundation for content based image retrieval in the domain of corrosion detection that is the ability to identify corroded structures from a large database of inspection images.

INTRODUCTION

A major concern of damage in steel power transmission lattice towers is corrosion. The transmission tower structures constructed using carbon steels are periodically painted to control corrosion. During the 1960's weathering steels of high strength and high strength low alloy compositions were being considered as an economic choice to achieve light weight overhead transmission towers (Goodwin & Joe, 1993). The improved corrosion resistance of the weathering steels allowed elimination of the necessity to galvanize and periodic painting. But, with the continuous presence of moisture, weathering steels acted like bare carbon steels. Currently there are a large number of transmission towers with carbon and weathering steels posing serious threats to bearing capacity of these towers due to corrosion. Timely inspection and repair are essential to avoid outages due to structural failure and to identify the corrosion damaged locations, cause of corrosion and corrosion type. This knowledge is necessary in planning suitable repairs for damaged elements and remedies to prevent further damage. The following types of corrosion damages encountered in the transmission tower (Mayer, 1998): General corrosion, Pitting corrosion, Crevice corrosion, Exfoliation corrosion, Stress corrosion, Corrosion fatigue, Hydrogen Embrittlement, Galvanic corrosion, Stray current corrosion, Coating damage and deterioration, and Microbial induced corrosion. The type of corrosion and extent of damage to an element due to corrosion are determined during field inspections through: 1) detailed visual inspection; 2) measuring loss of cross section; 3) measuring protective (galvanizing and /or paired) coating loss; and 4) Measuring contamination on surfaces (Mayer, 1998). Various destructive and non-destructive techniques are adopted for this purpose. Although these methods are successful, the inspection procedures have a few drawbacks. First, the substantial amount of time required for the inspectors to identify damage in each member of every structure in a large transmission network makes it expensive. Second, structures with existing damage are dangerous to access for inspection. Third, the accuracy of the methods often depends on the judgement and experience of the individual inspector. In such circumstances visual inspection of towers for corrosion issues is costly, time consuming; it is susceptible to inspector's errors making such methods undesirable. A viable option for damage detection is the automated inspection for corrosion using image processing techniques with aerial or ground based images.

The automation of corrosion detection using image processing has been subject of some research, which investigated image based automatic identification of corrosion and stages of corrosion damage in various kinds of structures. Medeiros et al (2010) distinguished corroded regions on pipelines from non-corroded regions using attributes from gray level co-occurrence matrixes (GLCM) and statistical attributes of Hue Saturation and Intensity (HSI) space of the images. The Fisher Linear Discriminant analysis algorithm was used for classification with an accuracy of 91%. The algorithm was trained using the attributes of a database of images for different stages of corrosion. Zaidan et al. (2010) discriminated corroded and non-corroded regions in image with texture analysis accompanied with edge detection, structure element and image dilation. Raman et al. (2013) identified the corrosion damage and quantified its different stages with time using the texture features such as energy and entropy from wavelet transform of the image and color features. The features were obtained from images of the accelerated corrosion experiments conducted on steel 304 panels. Woo et al. (2015) developed a toolset to measure the corrosion state of an individual member of the transmission tower using specialized camera and RGB statistics of the image.

The paper aims at automated detection of corroded regions in a power transmission lattice steel tower structures through image processing. The method also lays a foundation to detect the presence of corrosion damage in structures form a large database of images of the structures being inspected through content based image retrieval with unsupervised classification methods.

CORROSION IDENTIFICATION USING IMAGE PROCESSING

Many of the existing methods require extraction of corrosion related features form a large set of image database and train supervised classification algorithms to identify corrosion in a particular image. The current method uses a combination of unsupervised and supervised classification methods and does not require a large database of training images. The corrosion identification procedure is developed in MATLAB and is performed in two stages. First is the segmentation of the images based on color. Second and final is identification of any corroded segment in the image. These steps are explained in the following sections.

Image Segmentation: Based on the hypothesis that corroded region of a structure can be visually distinguished from the remaining structure and its back ground, the test image is initially segmented with respect to colors. For that, the test image is converted from RGB to CIEL*a*b* color space (Gonzalez & Woods, 2008). The L*a*b* color space is more convenient to work on color based segmentation as it quantifies the visual difference in colors similar to the perception of humans. Unlike RGB space it is device independent. It is a three dimensional space where "L*" axis corresponds to lightness or illumination with darkest at L*=0 and lightest at L*=100. The "a*" axis ranges from green at limit –a* and Red at limit +a*. Similarly "b*" axis ranges from blue at limit –b* and yellow at limit +b*. True neutral grey values on the axis are found at a* = 0 and b* = 0.

The a* and b* values of the L*a*b* space are reshaped into two columns and segmented into color clusters using *K-means clustering algorithm* (MATLAB, 2016). K-means clustering is one of the simplest unsupervised classification algorithms. It divides n dimensional data points in a dataset to a priori fixed K number of clusters such that a specified measure of distance between centroid and all the points in a cluster is minimum. For this K random points are chosen as initial centroids and the points in the entire dataset closest to the centroids are formed as a new cluster and the new centroids are calculated for each new cluster. The process is repeated iteratively to minimize the objective function corresponding to the combined sum of distance between centroids and data points in all clusters. In this case, squared Euclidean distance is used as distance measure and objective function is (Theodoridis, A., & Cavouras, 2010),

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2$$

Where $x_i^{(j)}$ is i^{th} data point in cluster j of centroid c_j. From experience K is fixed to 4 color clusters. Each of the pixel is color coded with its cluster number as shown in Figure 1(b). Each color segment of the actual image is individually extracted to separate RGB images and pixels corresponding to other clusters are black as shown in Figure 1 (c)-(d).

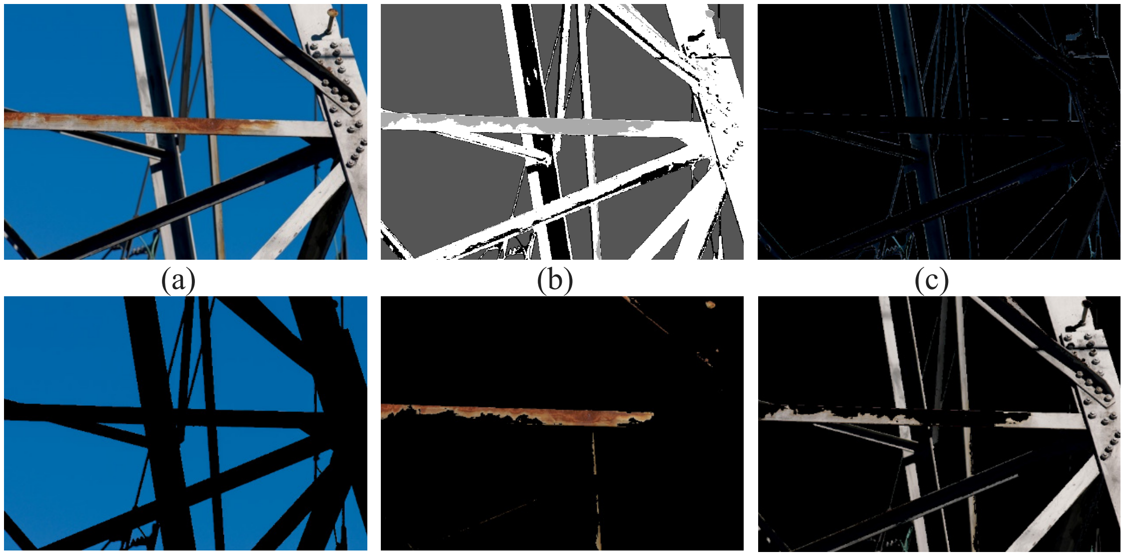


Figure 1 (a) Image of a lattice structure with corrosion. (Photo courtesy of PPG Industries, Inc.), (b) Image color indexed image based on clusters, (c) Segment of cluster 1, (d) Segment of cluster 2, (e) Segment of cluster 3 (f) and Segment of cluster 4.

Corrosion Identification*:* Segments corresponding to corrosion are classified based on their hue value characteristics. Unlike RGB space, the hue dimension in the HSV (Hue, Saturation and Value) space of an image can quantify every individual pure color (Gonzalez & Woods, 2008). On a scale of 0 to 1, the colors range from red through yellow, green, cyan, blue, magenta, and back to red with red at both 0 and 1 as shown in Figure 2. A set of 24 sample images of corroded steel surfaces at varying corrosion level and illumination are obtained and their hue frequency histograms on a scale of 0 to 1 are studied. As seen in the Table 1, there is at least 99.7% probability that values in the range of 0.2 to 0.5 hue are less than 0.01 for corroded surfaces. Whereas the value should be at least 0.1 in 0 to 0.1 interval which correspond to red hues. Individual color segments satisfying this condition are counted as corroded portion of the image. The flow chart in Figure 3 explains the procedure followed to identify the corroded region.

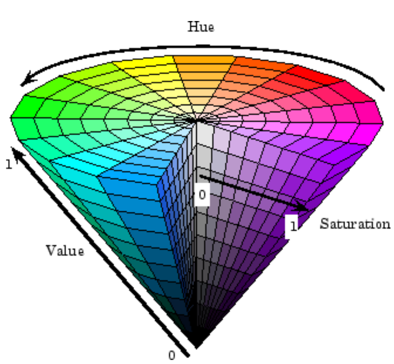


Figure 2 Illustration of HSV Color Space *(MATLAB, 2016)*.

Table 1. Statistics of Hue Value Histograms

Hue Range (0-1 scale)	Mean	Standard Deviation	99.7 % Probability of Not Exceeding
<0.1	0.8711	0.2413	1.5949
0.1 - 0.2	0.0080	0.0170	0.0589
0.2 - 0.3	0.0003	0.0010	0.0034
0.3 - 0.4	0.0007	0.0024	0.0080
0.4 - 0.5	0.0002	0.0007	0.0023
0.5 - 0.6	0.0013	0.0048	0.0158
0.6 - 0.7	0.0071	0.0187	0.0632
0.7 - 0.8	0.0136	0.0443	0.1466
0.8 - 0.9	0.0215	0.0630	0.2104
0.9 - 1	0.0014	0.0037	0.0126

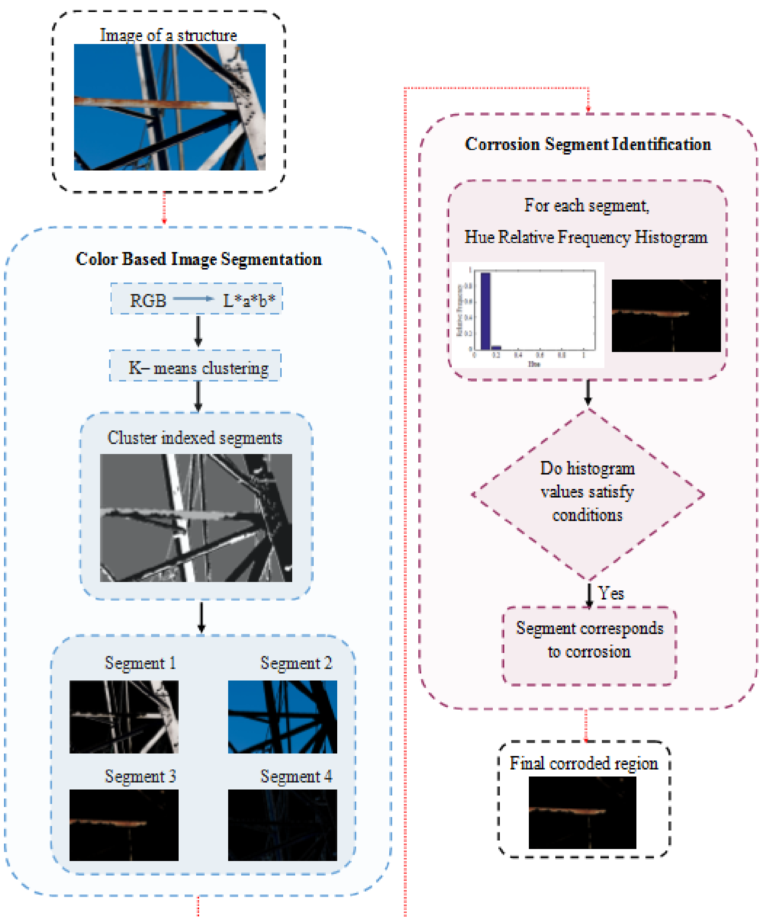


Figure 3 Flow chart showing procedure for automatic corrosion identification form a lattice tower structure.

RESULTS AND DISCUSSION

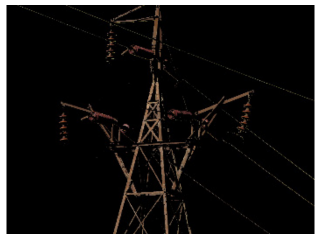
Unlike any usual case of image analysis, the images for inspection of structures like transmission towers are acquired under variable conditions. Considering this, corrosion identification procedure is tested upon a set of five images representing different parts in transmission tower structures and taking into account disparities in image data acquired during inspections such as distance from the structure, illumination, resolution and orientation. It is more relevant to express the performance of this method in the context of these disparities, qualitatively rather than quantitatively. The results for each of the test images are shown in Table 2.

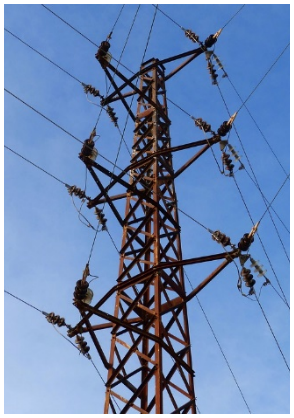
It is evident from the results of the test images in Table 2 that the procedure is successful in identifying corrosion in the image irrespective of the condition of image acquisition. In some cases non-corrosion region (false positives) are identified as corrosion in addition to the actual corroded regions (true positives) by the algorithm. One of the reasons is the insufficient number of clusters chosen for the K-means clustering algorithm, to separate color groups in the image to required degree. This is seen in the results of test images 3 and 4. The other case of false positives observed is due to the false identification of objects in the image with colors close to color groups of corrosion. Such instances are observed in results of the test images 2 and 5 where the insulators are included in the corrosion region. It is also to be noted that most of these images are acquired at either low resolution or at large distances form the actual structure, which increases their probability for mis-segmentation.

Some of these issues can be eliminated by pre-processing methods and by meeting certain image acquisition conditions. False positives due to objects in the background such as those experienced in test images 3 and 4 can be eliminated by subtracting the background of the structure in the pre-processing. Also, the false positives, usually insulators in case of transmission towers can be eliminated by shape based identification of insulators and elimination from the image along with the background given the images are acquired under previously described conditions. The problem with insufficient number of clusters can be dealt with automating the estimation of optimum number of K-means clusters.

The algorithm needs further refinement through testing on images form actual field surveys and expert opinions for identifying corrosion corresponding to a particular level of damage.

Table 2. Results of Images Tested for Corrosion Identification Procedure

	Test Image	Identified Corroded Region	Details
(1)			Corrosion in particular member of a galvanized structure.
(2)	 (Photo courtesy of Arresterworks)		Aerial image of top of the of the structure mostly affected by corrosion. False Positives: Insulators with hues close to corrosion
(3)	 (Photo courtesy of Osmose Utilities Services, Inc.)		Corrosion at the base. False Positives: Soil in the background.
(4)			Focusing only one of the corroded members. False Positives: Objects in the structure background due to insufficient color segmentation clusters.

	Test Image	Identified Corroded Region	Details
	(Photo courtesy of PPG Industries, Inc.)		
(5)	 (Photo courtecy of www.pixabay.com)		Image of coorded structure from ground. False Positives: Insulators with hues close to corrosion.

CONCLUSION

The proposed automated corrosion identification procedure for the power transmission lattice towers used unsupervised classification method of K-means clustering for color segmentation and features generated from hue statistics of each color segment to identify segment that corresponds to corrosion. The procedure is mostly successful in identifying corrosion except for some false positives, which can be avoided by necessary preprocessing, optimizing the cluster numbers and acquiring images at suitable conditions of resolution. With this, given a dataset of images of several transmission towers with each image tagged to a specific tower, the algorithm can extract specific images with corrosion. Hence, automatically identifying the transmission towers damaged by corrosion.

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