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Detection and quantitative assessment of corrosion on pipelines through image analysis

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Abstract

Pipeline is one of the safest and most reliable ways of hydrocarbon transportation. With a huge volume of process fluids (hazardous, flammable, corrosive, toxic) being handled, the integrity of pipelines is of the utmost importance to ensure safety of plant, people and environment. Corrosion on the external or internal surfaces of in-service pipes reduces the integrity of the pipeline system and potentially reduces the service life of the pipes. In order to automate inspection of pipelines over long ranges, a new methodology has been proposed using machine vision concepts. Corrosion is identified and the damage due to it has been quantified, which will help the management in maintenance of pipeline integrity to prioritize their remedial measures.

Keywords: Corrosion; Quantitative assessment; Image processing; Clustering.

1. Introduction

The oil, gas, chemical and petro-chemical industries operate on hundreds of kilometres of pipelines, often transporting hydrocarbons and non-hydrocarbons fluids (hazardous, flammable, corrosive or toxic). Each year, there are hundreds of pipeline failures, resulting into pollution, loss of transportation capacity, loss of oil and gas availability, and repair expenses.

These pipelines are prone to external corrosion, under support corrosion (crevices), corrosion under insulation (CUI), corrosion under painting and many other types of the same. Sometimes the corrosion may lead to cracking as

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well (known as Stress Corrosion Cracking). Therefore, inspection of pipelines at regular intervals and maintaining the integrity of pipeline system is a task of the highest priority.

The state-of–the-art inspection methods include magnetic flux leakage (MFL), ultrasonic testing, long range guided wave inspection, external corrosion direct assessment (ECDI) etc. All these methods have their own limitations, such as determination of stress corrosion cracking (SCC), limited range of inspection, finding small pitting defects, efficiency in identification of defects, and others. Inspection of a pipeline system ranging a few kilometres may not be efficient (more time consuming) using most of the existing methods. There is, therefore, an urgent need for the development of a quick, reliable method for the detection of corrosion in pipeline systems.

Some of the aforementioned problems in case of external corrosion can be solved using computer vision methods. Identification and quantification of corrosion done in various ways become extremely important to the management, especially in case the pipelines under inspection range over kilometres, as it is not practical to reach to each suspected location and perform maintenance operations. Besides this, quantification of corrosion gives the management an opportunity to give priority to the most damaged/critical regions among all the corroded locations in the plant.

The outline of the paper is as follows. In the next section, earlier studies related to identification of corrosion have been discussed. Section 3 introduces the proposed methodology for quantification of corrosion. Experimental results are discussed and analysis is carried out in section 4. Some concluding remarks are drawn in section 5.

2. Related Studies

Several methods were tried by various investigators, and some of those studies are discussed below.

Motamedi et al. [1] used image processing to detect the number of cracks and location of crack in the images of sheet metals. The images were captured with the help of a CCTV camera and a Line-Laser and processing of images had been carried out on MATLAB software.

Lohade and Chopadae [2] proposed a method for inspection of surface defects on metals including corrosion using image processing techniques. The images were captured using a Pi camera, which is a dedicated camera for raspberry Pi, and processing of images was carried out on raspberry Pi 2 processor. The acquired images were converted from RGB (Red, Green, and Blue) to HSV (Hue, Saturation, Value) colour space and a particular threshold value of an area based on colour of corrosion had been used to detect corrosion.

Ranjan and Gulati [3] studied the detection of corrosion on a metal using different edge detection operators and proposed a new method of detection using Canny edge detection technique and morphological operations like dilation and erosion.

Choi and Kim [4] made an attempt to identify the type of corrosion based on the morphology of the corroded surface. A sample of 197 images taken under optical microscope had been used for training and testing the classifier. Eighteen attributes, which represent colour, texture and shape, were used as the features. Feature space was reduced to 2-dimensions using multidimensional scaling (Principal coordinate analysis) and classification of the types of corrosion was carried out using linear classifiers.

Medeiros et al. [5] investigated the classification of corroded and non-corroded surfaces using texture descriptors obtained from GLCM (grey level co-occurrence matrix) and colour descriptors obtained from statistical moments in HSI (Hue, Saturation and Intensity) colour space.

One of the first attempts to quantify pitting corrosion using digital image processing was done by Itzhak et al. [6]. Pitting probability defined as the ratio of number of pixels containing in pit to total number of pixels was evaluated for AISI 304L stainless steel after subjecting it to $FeCl_3$ solution.

Ji et al. [7] proposed a method based on computer vision for rating of corrosion defects on coated materials using watershed segmentation method. They suggested a method of evaluating the area of corroded image and percentage area of corroded image to grade the defects.

From the above literature, it may be concluded that a significant amount of research was carried out in corrosion identification using image processing and machine learning tools but a very little work was done on quantification of the corrosion on pipelines. In this paper, an attempt is made to quantify corrosion on the surface of a pipe and locate the most critical regions on the pipe.

3. Methodology

The steps followed in the proposed methodology to detect and quantify corrosion are as shown in Fig.1.

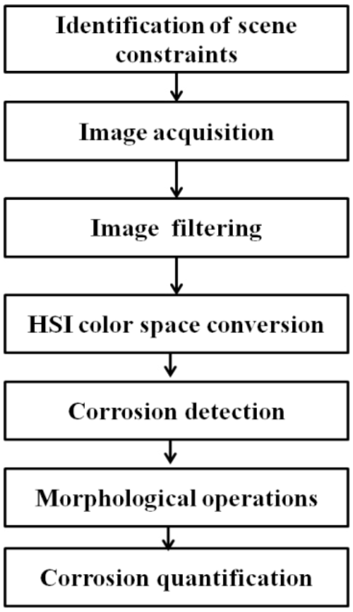

Fig. 1. Steps adopted for corrosion detection and quantification process.

Fig. 2. Sample image captured using mobile phone camera.

3.1. Identification of scene constraints

The most important step in developing any industrial machine vision system is to identify the existing environmental constraints, so that complexity of vision system gets reduced and further processing of images becomes faster [8]. The identified constraints guide us in choosing suitable algorithms and methods in developing an efficient vision module.

The scene constraints that can be easily identified during pipe inspection are as follows:

- Color of pipe's outer surface and that of corrosion on the pipe.
- Different objects typically present in a captured image, such as pipe, corrosion on pipe and background.
- Camera can be constrained to focus and capture only outer surface of the pipe under inspection.

The first constraint indicating the color of the corrosion is crucial in detection and quantification of corrosion in a given image. The second and third constraints can be used in distinguishing pipe from background, and so aid in capturing only outer surface of the pipe.

3.2. Image acquisition

The images of a corroded metallic pipe are captured using a mobile phone camera of 8 Mega pixel resolution during day light. Background of the pipe image is not captured deliberately, so that analysis of the pipe surface becomes easier. A sample image captured is shown in Fig. 2.

3.3. Removal of noise by image filtering techniques

Sometimes, captured images may be contaminated with noise for various reasons. This usually occurs during image acquisition or image transmission. Depending on the noise present in the image, appropriate filtering technique needs to be performed on the image before analyzing it. For example, median filtering technique can be used to remove salt and pepper noise present in an image.

3.4. Transformation of color space from RGB to HIS

Identification of corrosion in the image in RGB color space becomes computationally expensive and cumbersome, as the chromatic component of the image can only be obtained using information from all the three channels, namely red, green and blue. A gray scale image, as shown in Fig. 3(a), cannot be used readily to identify the corrosion in RGB color space. In order to avoid this problem, the given image is transformed into HSI (Hue, Saturation and Intensity) color space, where the chromatic and achromatic components of the image can be readily distinguished. Saturation component of the image obtained in Fig. 3(b) can be readily used for detection of corrosion.

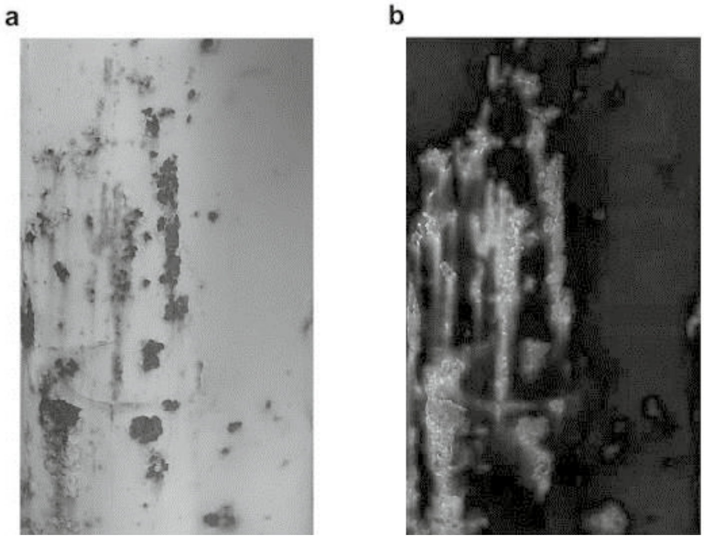

Fig. 3. (a) Grey scale image of the original image; (b) Saturation component of the original image.

Conversion of an image from RGB color format to HSI color space is carried out using the equations given below [9].

$$H = \begin{cases} \theta & if \;\; B < G \;, \\ 360 - \theta & if \;\; B > G \;, \end{cases} \tag{1}$$

$$\text{where} \;\; \theta = \cos^{-1}\left\{ \frac{\frac{1}{2}\left[(R-G)+(R-B)\right]}{\left[(R-G)^2+(R-B)(G-B)\right]^{1/2}} \right\} .$$

$$S = 1 - \frac{3}{(R+G+B)}[\min(R,G,B)] . \tag{2}$$

$$I = \frac{1}{3}(R+G+B) . \tag{3}$$

RGB values should be normalized to the range of [0, 1] and the angle is measured with reference to red axis of the HSI color space.

3.5. Corrosion detection

In order to determine whether the pipe is corroded or not, mean of saturation value of all pixels is computed. If computed mean value is found to be greater than particular threshold value, corrosion is detected. This is obvious from the fact that corroded surface has the higher value of saturation component than that of the surface of metal, which is generally painted in light colors like grey or white [5].

The threshold can be chosen empirically and it is mainly application dependent. The higher or lower threshold can be selected depending on the functionality of the pipe and severity of damage due to pipe failure.

3.6. Morphological operations and quantitative assessment

Once the corrosion is detected, the final step is to quantify the corrosion in various ways, so that it becomes easier to identify the most critical region, and some hypothesis can be made on the nature of corrosion based on the distribution of corrosion on the pipe.

The following measures have been computed to quantify corrosion.

3.6.1. Percentage of corrosion

This is measured as follows:

$$\% \text{ of corrosion} = \frac{\text{Number of corroded pixels}}{\text{Total number of pixels used to represent the pipe}}$$

The number of pixels identified as corroded depends on the threshold chosen and so the percentage of corrosion is measured considering four distinct thresholds.

3.6.2. Percentage of area damaged due to corrosion

It is well-known that the regions surrounding the corroded regions are prone to be corroded easily. In order to determine the number of pixels gets affected due to corrosion, it is assumed that all the pixels in the neighbourhood of a corroded pixel are considered to be damaged. This is computed as follows:

$$\% \text{ of damaged area} = \frac{\text{Total number of pixels lying in } 5\times 5 \text{ neighbourhood of all corroded pixels}}{\text{Total number of pixels used to represent the pipe}}$$

This measure is also dependent on the threshold chosen and has been computed for four distinct thresholds.

3.6.3. Identification of the most damaged/critical regions using k-means clustering algorithm

There may exist many regions on a pipe, where corrosion is detected, but there will be a few locations, where the severity of the damage is high and these locations need immediate attention. It is assumed that saturation component of the pixel is proportional to the severity of the damage and accordingly, the regions having the higher saturation values are identified as the most damaged ones.

Identified critical regions are considered as a two-dimensional dataset and morphological operations have been carried out to remove the pixels in less density regions. These pixels are considered to be the outliers or noise for clustering, so that location of dense regions becomes easier.

In order to remove the external noise present in the image, a morphological operation called opening (erosion followed by dilation) has been performed on the image with a disk shaped structuring element [9]. In order to remove the internal noise present in the image, closing operation (dilation followed by erosion) has been performed on the processed image with the same structuring element.

4. Results and Discussion

4.1. Corrosion detection

To detect corrosion in a given image, threshold value for mean saturation component of an image is empirically chosen as 0.05. Actual computed value of mean is 0.1273, which is much higher than the chosen threshold. So, it is a strong indication of the presence of corrosion. Only if corrosion is detected, the image will be further analyzed to obtain various corrosion attributes.

4.2. Corrosion quantification

Corrosion has been quantified in a number of ways, as discussed below.

4.2.1. Percentage of corrosion

The corrosion observed, after thresholding saturation component of the image with different values, is shown in Fig. 4, where t is the mean value of saturation component of the image. It is obvious that if a higher threshold is used, the number of pixels identified as corroded ones decreases and so, the percentage of corrosion also decreases, as shown in Table 1.

In order to validate the percent of corrosion obtained through image analysis, it is essential to measure the percent of corrosion physically and compare both the results. However, since the corrosion is generally spread throughout the surface of pipe, measuring it for a particular threshold of saturation component is not practically possible. So, physical measurement has been carried out by printing the binary images for the four different thresholds on a standard A4 sheet paper and percent of area is approximated as the ratio of the weight of corroded portion on the sheet to weight of the whole paper. It is observed that the percent of corroded area obtained through physical measurement is slightly higher than that of the area obtained through image analysis. This is due to approximation of the corrosion locally by closed boundaries in order to measure the weight of the corroded portion on the paper.

Table 1. Percentage of area corroded for different thresholds

Sl. No.	Threshold of saturation	Number of pixels corroded	% of area corroded (from binary image)	% of area corroded (through physical measurement)
1	t	88576	26.68	29.59
2	$2t$	52784	15.90	17.27
3	$3t$	26232	7.90	9.41
4	$4t$	8206	2.47	3.65

4.2.2. Percentage of area damaged due to corrosion

The percentage of area damaged due to corrosion has been computed for four different threshold values considering three distinct neighbourhood sizes around the pixel for each threshold. It is observed that the percentage of damaged pixels is inversely proportional to threshold value and directly proportional to neighbourhood size around a pixel. The computed values of damaged area are shown in Table 2.

Table 2. Percentage of area damaged for different thresholds and different neighborhoods around the corroded pixel

Sl. No.	Threshold of saturation	Number of pixels damaged (5x5 window)	% of area damaged` (3 x 3 window)	% of area damaged` (5x 5 window)	% of area damaged` (7 x 7 window)
1	t	101659	28.04	30.63	33.11
2	$2t$	65972	17.31	19.87	22.24
3	$3t$	39489	9.33	11.90	14.23
4	$4t$	18046	3.46	5.44	7.31

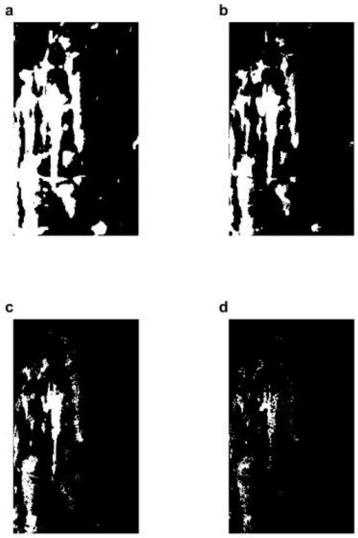

Fig. 4. Binary images obtained after thresholding saturation component of original image: (a) threshold of mean of saturation value of original image (t); (b) threshold of $2t$; (c) threshold of $3t$; (d) threshold of $4t$.

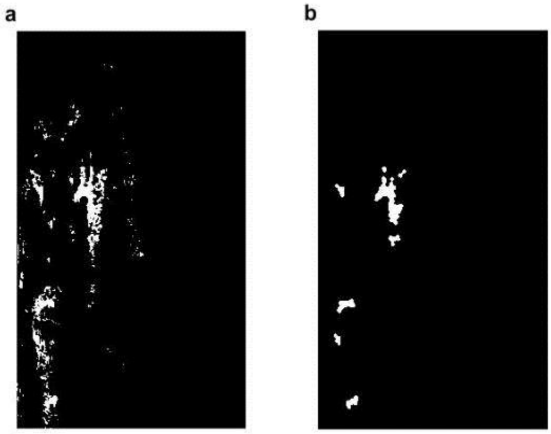

Fig. 5. (a) Image obtained after thresholding saturation component of image with higher threshold; (b) Image after carrying out opening and closing operations on Fig. 5. (a).

4.2.3. Identification of the most damaged/critical regions using k-means clustering algorithm

In order to locate the critical regions among all the corroded ones on a pipe surface, a threshold of 0.7 times the maximum value of saturation in the image has been empirically chosen. The identified critical regions after thresholding operation are shown in Fig. 5(a). Morphological operations like opening and closing are applied to locate highly dense regions. These operations lead to an increase in cluster tendency of the pixels, as shown in Fig. 5(b).

Standard k-means clustering algorithm is applied to identify the centers of the dense regions, so that conventional pipe inspection methods can be directly performed at these locations. The number of clusters to be formed is kept equal to six ($k = 6$) and centers of the cluster are identified, as shown in Figs. 6 and 7. Although the location of cluster centers depends on the initial points chosen as centers, the locations identified will serve the main purpose behind clustering the data.

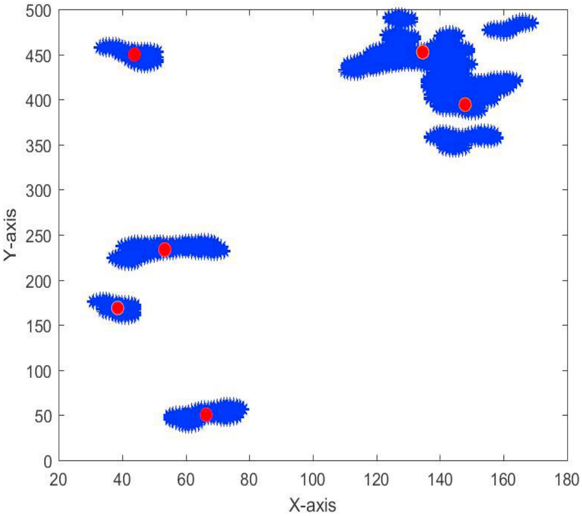

Fig. 6. Centers of the clusters computed using k-means clustering algorithm.

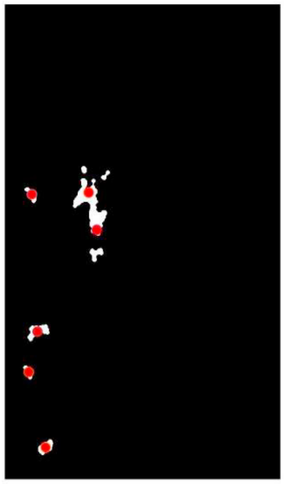

Fig. 7. Location of densely corroded regions on the original image.

5. Conclusion and future work

A novel method has been proposed for detection and quantification of corrosion on a pipe using digital image processing techniques. Detection is carried out by deliberately capturing only the surface of the pipe and applying threshold on mean saturation value of an image. Quantification is carried out by measuring corrosion area, damaged area and by locating the centers of the densely corroded regions in the image.

In order to increase the robustness of detection of corrosion, other features related to texture and shape can be used in future work. To automate detection and quantification in real life applications, the parameters for any chosen clustering algorithm can be automatically computed through cluster stability analysis and cluster validation methods .

References

[1]. Motamedi M, Faramarzi F, Duran O. New concept for corrosion inspection of urban pipeline networks by digital image processing. Paper presented at: IECON 2012-38th Annual Conference on IEEE Industrial Electronics Society; 2012 Oct 25; Montreal, QC: IEEE; 2012. p. 1551-1556.

[2]. Lohade DM, Chopade PB. Real Time Metal Inspection for Surface and Dimensional Defect Detection Using Image Processing Techniques. Paper presented at: EEECOS-2016 – 3rd International Conference on Electrical, Electronics, Engineering Trends, Communication, Optimization and Sciences; 2016 June. p. 873-877.

[3]. Ranjan, R.K., Gulati, T.: Condition assessment of metallic objects using edge detection. Int. J. Adv. Res. Comput. Sci. Softw. Eng. 2014; 4(5):253-258.

[4]. Choi KY, Kim SS. Morphological analysis and classification of types of surface corrosion damage by digital image processing. Corrosion Science. 2005 Jan 1; 47(1):1-15.

[5]. Medeiros FN, Ramalho GL, Bento MP, Medeiros LC. On the evaluation of texture and color features for nondestructive corrosion detection. EURASIP Journal on Advances in Signal Processing. 2010 Dec 1; 2010(1):817473.

[6]. Itzhak D, Dinstein I, Zilberberg T. Pitting corrosion evaluation by computer image processing. Corrosion Science. 1981 Jan 1; 21(1):17-22.

[7]. Ji G, Zhu Y, Zhang Y. The corroded defect rating system of coating material based on computer vision. In Transactions on Edutainment VIII 2012 (pp. 210-220). Springer, Berlin, Heidelberg.

[8]. Awcock GJ, Thomas R. Applied image processing. London; McGraw-Hill, Inc.; 1995 Sep 1.

[9]. Gonzalez Rafael C, Woods Richard E, Eddins Steven L. Digital image processing using MATLAB. Editorial Pearson-Prentice Hall. USA. 2004.