Article

Journal of Engineering Applications

December 2021, Vol.8 No.26 7-13

Image segmentation with K-Means and color-manipulation techniques for the identification of corrosion patterns

Segmentación de imágenes con K-means y técnicas de manipulación de color para la identificación de patrones de corrosión

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DOI: 10.35429/JEA.2021.26.8.7.13 Received: July 15, 2021; Accepted: December 30, 2021

Abstract

This article presents an experimental case study on images of corroded metal surfaces, which are processed and segmented using the K-means algorithm and color-manipulation techniques such as Grayscale, HSV, RGB, and CIE L*A*B*. The objective of this research is to identify corrosion patterns on processed metal surfaces, providing experts with a basis for decision-making. Papers related to image segmentation of areas or surfaces with corrosion always subject the results obtained to a second or third manual analysis, which means spending more time and resources on analysis. In the research presented here, the results obtained show that preprocessing the test images, separating the layers of the images into color spaces, and then processing and segmenting them with the K-means algorithm can offer different perspectives with each technique implemented and can speed up the assessment time and mark off the area showing corrosion damage on the metal surface under analysis.

K-means, Image segmentation, Pattern recognition

Resumen

En este artículo se presenta un caso de estudio experimental sobre imágenes de superficies metálicas corroidas, mismas que son procesadas y segmentadas con el algoritmo K-means y por técnicas de manipulación de color como Escala de grises, HSV, RGB y CIE L*A*B*. El objetivo de esta investigación es la identificación de patrones de corrosión en las superficies metálicas procesadas, brindando a los expertos un soporte en la toma de decisiones. En trabajos relacionados con la segmentación de imágenes en áreas o superficies que presentan corrosión, se ha identificado que los resultados obtenidos son sometidos siempre a un segundo o tercer análisis manual, lo que representa consumo adicional de tiempo y recursos para el análisis. En esta investigación, los resultados obtenidos muestran que al preprocesar las imágenes de prueba, separando las capas de estas imágenes en espacios de color, y posteriormente procesandolas y segmentandolas con el algoritmo K-means, se pueden ofrecer diferentes perspectivas con cada técnica implementada y acelerar el tiempo de evaluación y delimitación de la zona que presenta el daño por corrosión en la superficie metálica analizada.

K-means, Segmentación de imágenes, Reconocimiento de patrones

Citation: ALMANZA-ORTEGA, Nelva Nely, MARTÍNEZ-AÑORVE, Héctor G., FLORES-VÁZQUEZ, Juana María and PÉREZ-ORTEGA, Joaquín. Image segmentation with K-Means and color-manipulation techniques for the identification of corrosion patterns. Journal of Engineering Applications. 2021. 8-26:7-13.

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Introduction

The problems caused by corrosion can vary, ranging from economic losses and irreparable harm to the ecosystem to the loss of human lives. For example, if a hydrocarbon pipeline is deteriorated or defective due to corrosion, the result could be structural damage, a leak, or even an explosion.

Given that corrosion is an important phenomenon that causes considerable economic losses and can even directly or indirectly result in the loss of human lives, we propose a method in this paper for identifying corrosion patterns in different types of corroded metal surfaces. Finding these patterns will help the decision-making process regarding infrastructures that may require preventive, corrective, or emergency maintenance.

Related studies show an important interest on the part of those working in technological fields in providing experts and decision makers with tools to help mitigate these types of situations. Along these lines, the field of artificial intelligence (AI) has contributed algorithms that can recognize corrosion damage and segmentation algorithms that use different techniques for corrosion recognition.

Our research focuses on preprocessing a test image set, separating these images' layers into color spaces, and then processing and segmenting them with the K-means algorithm. The objective is to offer different perspectives with each technique and to speed up the time spent evaluating corrosion damage to the metallic surface under analysis.

To present our proposal and the results obtained, this paper is organized as follows. In the section on the theoretical framework and related papers, the main concepts of corrosion, image segmentation, and the color-manipulation techniques used in the experiments are laid out. The methodology section describes the repository from which the test image set was obtained and the procedure for carrying out the experiments is presented.

In the analysis-of-results section, the relevant findings and the important patterns obtained from the processed images are presented. In the conclusions section, we address the benefits of applying the K-means algorithm for image segmentation and the color-manipulation techniques on corroded metal surfaces.

Theoretical framework and related papers

Corrosion is a complex phenomenon involving the dynamics of coupled chemical, electrochemical, biological, and solid-state reactions and environmental chemistry (Scully, 2019; Sander, 2018). A common way of classifying corrosion types is as follows (Salazar-Jiménez, 2015):

a) Generalized corrosion

b) Localized corrosion

c) Corrosion combined with a physical phenomenon.

Corrosion is highly important due to the financial costs incurred by prevention, structural inspection, and maintenance, as well as the social and environmental risks it can entail. According to (Issam, 2014), direct losses due to corrosion are estimated to be $276 billion per year, or 3.1% of the gross domestic product of the United States. Additionally, in Guadalajara, Mexico, on April 22, 1992, there was an explosion caused by gasoline fumaroles from a leaking steel pipe, causing the death of 12 individuals. In the United States in 1967, pitting corrosion was the cause of the collapse of the U.S. Route 35 Bridge, which caused the death of 46 individuals (Long, 2019).

Due to these types of events, papers and research have been published that involve the formulation of complex experiments supported by machine learning, which could lead to designing new structural and functional materials with improved corrosion properties (Scully, 2019). Besides the creation of new materials, there is machine-learning research dedicated to the development and implementation of image-segmentation algorithms with the goal of identifying and recognizing patterns (Carpio, 2021; Coca-Castro, 2021; Lozano, 2021; Vila, 2021; Zia, 2021).

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Among related papers that have implemented machine-learning techniques and color techniques for corrosion identification is (Choi, 2005), who forms a corrosion color characterization and uses the HSI method for its detection to process the image. (Motamedi, 2012) implemented the smoothing and thresholding method for processing an image set and detecting the number and location of cracks in metal sheets. To represent the material in a way that emphasizes contrasts and highlights the important areas, (Mohammadpoor, 2020) uses the K-fold validation method and (Bondada, 2018) uses grayscale. (Ranjan, 2014) uses the edge detection technique to identify points at which an image suddenly changes in brightness or shows discontinuities. (Liu, 2019) presents agricultural-image segmentation using Fuzzy C-means. (Dubey, 2013) implements CIE L*A*B* and K-means to segment the infected parts of fruit. Because of the techniques used, this latter paper is closest to our research in its use of the K-means algorithm, which is one of the most popular clustering algorithms.

Methodology

In carrying out this research, we will use a modular experimental approach, which consists first in the identification of a repository from which we will obtain images of metal surfaces with corroded areas. Once we have the images, they will be preprocessed with color-manipulation techniques and then be processed with the K-means algorithm. The K-means algorithm will generate the image-segmentation models, allowing us to assess the ones that offer the best pattern identification and recognition. In this particular case, the pattern will be the segmentation of the area that shows corrosion.

Collection of images

Different public-access data sources are available for obtaining images. In our case, the repository from which we got the images for carrying out our research was the Mendeley Repository (Mendeley, 2021). The repository's platform is on the cloud, and it manages and stores large quantities of research data that are available for reproducing experiments or for new developments, guaranteeing in this way that they will be easy to share, access, and cite.

For the purposes of reference, a Digital Object Identifier (DOI) is generated for the data, which is maintained for citing datasets or resources in a standardized way. For our experiments, we used the Corrosion_Data Set, which can be accessed via the following link:
https://data.mendeley.com/datasets/tbjn6p2gn9/1/files/c311d38e-f04d-41ff-a508-dba6b60cc07b.

Figure 1 shows one of the images obtained from the test set that will be used to present the relevant research results obtained.

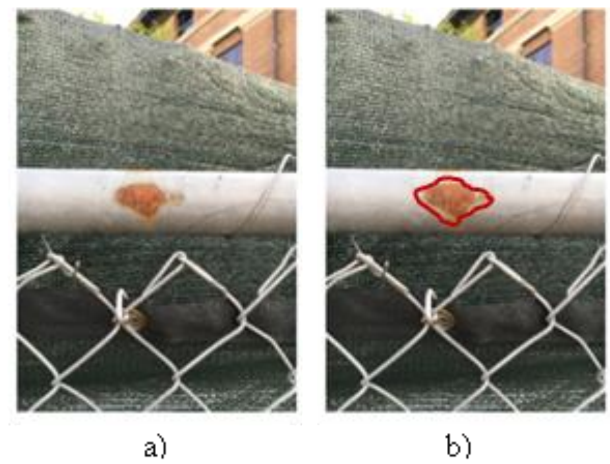

Figure 1 Test image for the experiment

Figure 1 a) shows the original image, and Figure 1 b) highlights the area with corrosion, which we want to be identified as a corrosion pattern once it is processed with the K-means algorithm.

Once we have the image, it will be manipulated according to the methodological process presented in Figure 2. The objective of using this type of experimental architecture is to speed up the process of getting fast models or prototypes that give us different assessment models for decision-making.

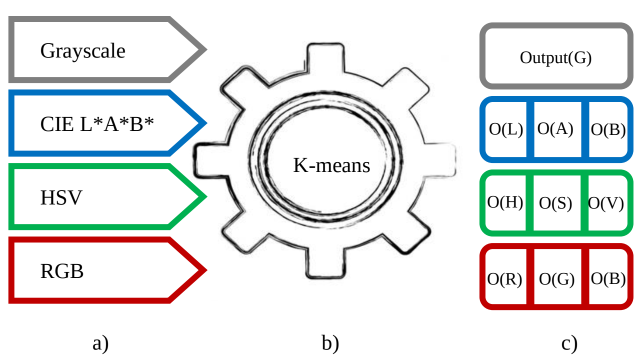

Figure 2 Methodology and development process

ISSN: 2410-3454

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The procedure sequence shows that the test image will be preprocessed by a set of color-manipulation techniques to separate the color spaces, as is shown in Figure 2 a). Each space image is then segmented with the K-means algorithm, as shown in Figure 2 b). Finally, models for assessing the corrosion-area patterns are obtained in Figure 2 c).

Image preprocessing

To preprocess the test images, four color-manipulation techniques are used to simplify the image analysis. The techniques that were employed are briefly described below.

Grayscale. Preprocessing an image in grayscale requires a two-dimensional matrix that records information regarding the intensity of light at each of the image's points. This is done for the purpose of extracting the features of each analyzed image (Burger, 2010).

CIE L*A*B*. This technique is defined as a uniform color space where the color stimuli are identified by the letters L*, A*, and B*. Its components' definitions are as follows: *L* represents the quantity of light or lightness and depends on tristimulus data. *A* contains the green and red color information, and *B* contains the blue and yellow color information (Eissa, 2013).

HSV. This abbreviation stands for Hue Saturation Value. This technique is used to analyze images' hue intensity. Every color space is studied as a quantitative analytical parameter for bitonal optic sensors (Cantrell, 2010).

RGB. This technique is the result of the representation of light's primary trichromatic components (red, green, and blue) on a Cartesian coordinate system. The color distribution in this technique is not balanced. To represent each of the image's pixels, the color intensity is defined as a whole number between 0 and 255 (Maia, 2016).

Training the models

The algorithm used for image segmentation is the K-means clustering algorithm. This algorithm's objective is to partition a dataset in k groups in such a way that the objects of each group are similar to one another but different from the objects of other groups. These groups are known as clusters (Jain, 2010).

The image-segmenting procedure is as follows:

Step 1: Load the image and convert it to a pixel matrix within a column of vectors.

Step 2: Randomly choose k pixels from the matrix generated in Step 1 as initial centroids.

Step 3: Assign each pixel to the nearest centroid's cluster.

Step 4: Calculate the average distance of the pixels belonging to each cluster and update the centroids with the newly calculated average.

Step 5: Repeat steps 3 and 4 until the stopping criteria are met.

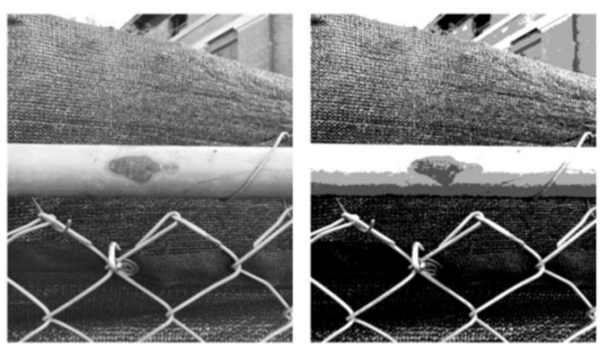
The color-manipulation techniques and the K-means algorithm were run with the native functions implemented in Python and the experiment was carried out in the Anaconda environment.

Analysis of results

This section presents the analysis of the results obtained from the experimental process shown in Figure 2.

Grayscale + K-Means

Figure 3 shows the model obtained by preprocessing the image with the grayscale technique and then processing it with the K-means algorithm, forming four color clusters.



a) b)

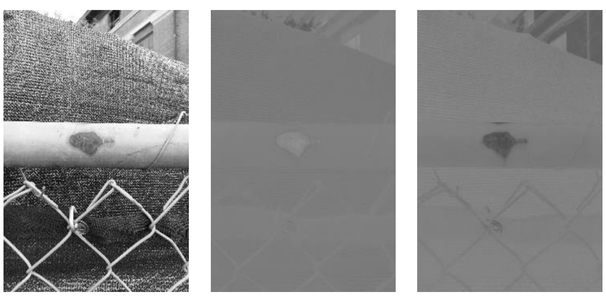
Figure 3 Grayscale + K-means with $k = 4$

ISSN: 2410-3454

Figure 3 a) shows the preprocessed image. We can see how applying this technique reduces the light's intensity so that it is not a noise factor when processing the image with the K-means algorithm. Nevertheless, we can see in Figure 3 b) how the corrosion area is distorted by two layers that make it look like the corroded area is spread all along the metal pipe. The inner layer is fainter than the one representing the corrosion and not as faint as the one that defines the pipe's surface. With this model, we can see right away that the analysis and identification of the affected area is more complicated, because it looks like more of the pipe is corroded than in fact is.

*CIE L*A*B* + K-Means*

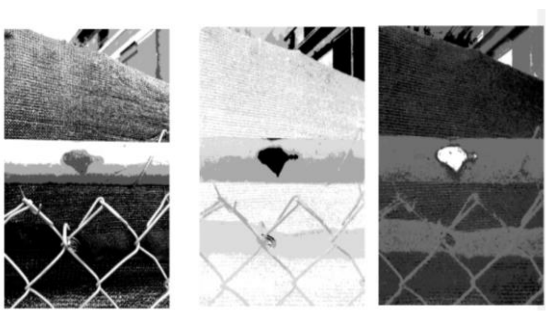
Figure 4 shows the image after applying color-space separation using the CIE L*A*B* technique. Figure 4 a) shows the lightness space, Figure 4 b) shows the space of the green and red colors, and Figure 4 c) shows the space of the blue and yellow colors. With the separation of colors into spaces, we see that the space that best defines the corrosion area is in Figure 4 c), which represents blue and yellow.



a) L* b) A* c) B*

Figure 4 Image preprocessed with CIE L*A*B*

Figure 5 shows the models obtained after processing each color space separately with the K-means algorithm and forming four color clusters for each model.



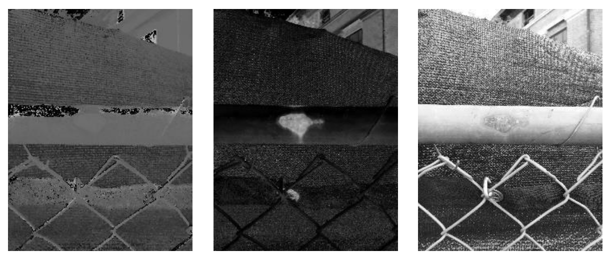
a) L* b) A* c) B*

Figure 5 CIE L*A*B* + K-means with $k = 4$

The models in Figures 5 b) and c) provide better definitions to the corrosion area. In both models, the affected area is strongly contrasted with the rest of the image. With these two models, the analysis of the entirety of the corroded surface is simple and clear. On the other hand, we can see in Figure 5 a)'s color space, which is the model that was preprocessed with lightness, that there are distortions similar to those obtained using Figure 3 b)'s grayscale technique.

HSV + K-Means

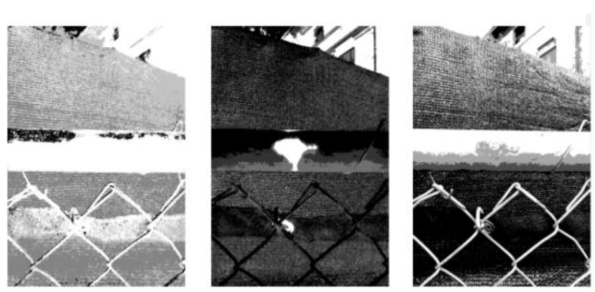
Figure 6 shows the image after applying color-space separation with the HSV technique. Figure 6 a) shows the Hue space, Figure 6 b) shows the Saturation color space, and Figure 6 c) shows the Value space. With this separation, we see that the space that best defines the corrosion area is that of Figure 6 b), which, due to the color saturation, marks off the area well.



a) H b) S c) V

Figure 6 Image preprocessed with HSV

Figure 7 b)'s model shows a better definition of the corrosion area. Although in this model there is a variation of layers on the metal pipe, the corroded area can be very clearly seen. In the case of the models in Figure 7 a) and c), the corrosion area is practically invisible and nearly impossible to identify. It is important to mention that, from the preprocessing, we already had sufficient information to identify the corrosion pattern on the surface.

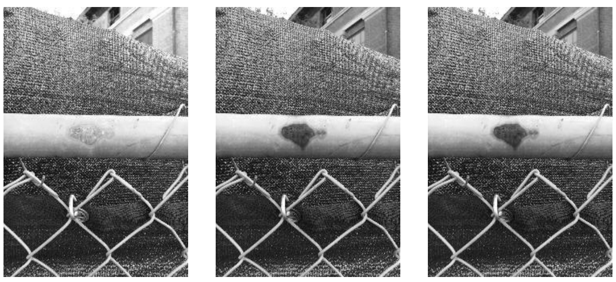


a) H b) S c) V

Figure 7 HSV + K-means with $k = 4$

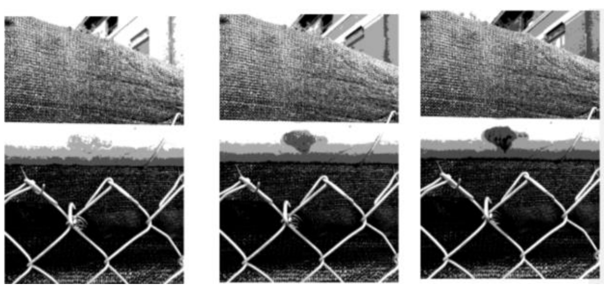
RGB + K-Means

Figure 8 shows the image after applying color-space separation with the RGB technique. Figure 8 a) shows the red space, Figure 8 b) shows the green space, and Figure 8 c) shows the blue space. With the separation into color spaces, we see that the space that best defines the corrosion area is Figure 8 b) and Figure 8 c), which represent the green and blue colors.



a) R b) G c) B

Figure 8 Image preprocessed with RGB



a) R b) G c) B

Figure 9 RGB + K-means with $k = 4$

The models in Figure 9 b) and c) show a better definition of the corrosion area. However, as happened with the grayscale technique, the metal pipe’s surface is marked with two layers of shadow that introduce noise into the image and could cause confusion when doing analysis. When compared to the original, it is Figure 9 c) that presents the best definition of the corrosion pattern.

Thanks

MSc student Héctor G. Martínez Añorve would like to acknowledge his scholarship (Recipient No. 782708) awarded by the Consejo Nacional de Ciencia y Tecnología [National Science and Technology Council], Mexico.

Conclusions

This paper proposes the use of color-manipulation techniques for preprocessing an image before it is processed and segmented by the K-means algorithm. The purpose of image processing is to identify and find corrosion patterns on metal surfaces.

The results show that it is possible to obtain important results from the preprocessing of images. Specifically, the experimental results obtained with the test image show that the techniques that provide a better definition of the corroded area are the CIE L*A*B* and HSV techniques.

Once the images were processed and segmented with the K-means algorithm, the corrosion pattern is maintained and a higher contrast is obtained against the rest of the image. This experiment shows that it is possible to reduce processing time for the analysis of corroded metal surfaces. This methodology expands the opportunities and fast models or prototypes that can be presented to experts for decision-making. These models speed up assessment times and are supported by techniques and algorithms able to generate production models and obtain fast results that support decision-making, improve business, and provide tools should it be necessary to reconsider strategies.

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