Enhanced Corrosion Detection By Means of Multispectral Imaging and Postprocessing Techniques

William V. Giegerich*, Dennis C. Fedorishin, Livio Forte III, Liam Christie, Philip J. Schneider, Kwang. W. Oh*

*SMALL (Sensors and MicroActuators Learning Lab) Department of Electrical Engineering The State University of New York (SUNY at Buffalo), Buffalo, NY, 14260, USA
Emails : wvgieger@buffalo.edu (Williams Giegerich), kwangoh@buffalo.edu (Kwang. W. Oh)

ABSTRACT

This research focuses on the implementation of an enhanced corrosion detection algorithm using multispectral imaging techniques and post-processing image filters. Utilizing various combinations of light filters with image enhancement software, we are able to increase the performance of a pixel-wise corrosion detection algorithm in both recall and precision, increasing the F1-Score of rust pixels detected from 0.33 to 0.60. Identification and quantification of corrosion was applied to applications relating to material characterization and automotive diagnostics.

Keywords: corrosion detection, multispectral imaging, post-processing

1 INTRODUCTION

Corrosion is an electrochemical reaction that takes place between a material and its environment. Environmental factors influence the rate of oxidation, which results in a degradation of the material properties. Frequently seen in industrial applications such as civil structures, machinery equipment, and automotive, corrosion build up is also prevalent in micro-electromechanical systems and sensor technology where it can lead to a decreased component lifespan [1]. Oxidation corrosion, commonly known as rust, can take a variety of forms and from that respect it is important to have an understanding of its various classifications when characterizing a material. An in depth understanding of rust characterization can be seen in [2]. In the automotive industry, rust on a vehicle is a major consideration when evaluating the structural integrity of the vehicle's frame. For instance, a vehicle could have surface rust, which is typically an early stage of rust that exists primarily on the exterior of the metal and is frequently a cosmetic issue. A more advanced stage of corrosion is called scale rust. In this case, rust will begin to blister on a substrate eventually peeling the protective surface finish away. Thirdly, there is penetrating rust. At this point corrosion has occurred through the entire thickness of the material, often creating holes, which ultimately compromise the structural integrity of the material.

The identification and quantification of rust has been an area of research as a result of its negative impact to the structural integrity of the material. Identification of rust is traditionally done in person by trained personnel with specialized equipment. Efforts have been made to automate that process through image processing algorithms [3]. These algorithms primarily focus on the image characteristics for texture and color by utilizing red/green/blue (RGB) color space, hue saturation intensity (HSI), and hue, saturation, value (HSV). Nash et al. demonstrated the use of computer vision and machine learning techniques to better detect corrosion on electrical components [4].

The goal of this study is to leverage these imagery post-processing techniques to quantify improvements in the detection and identification of rust on a substrate.

2 METHODS

For this study our focus is on rust detection in the automotive sector. A baseline image with known penetrating and surface rust is first selected. To establish a ground truth for the image, areas with rust are manually labeled on the picture at the per pixel level. The raw unaltered picture is then sent through a color detecting algorithm that identifies any pixel that falls within the color spectrum range associated with rust in the HSV color space. The rust pixel count is then recorded for the raw image. The process flow for the creation of the ground truth image can be seen in Figure 1.

Figure 1: Ground truth generation process used as a baseline comparison. Where (a) Is the raw image used for analysis (b) is the user selected areas containing rust (c) is the extracted rust area from the image (d) is the binarized image containing the highlighted rust.

Once established, the raw image is sent through a combination of post processing enhancements, using "Polarr Photo Editor"[1] and Python. Image post-processing techniques modified the range of characteristics for saturation, sharpness, contrast, color, vibrance, luminance, dehase, clarity, and highlight. 60 different individual filters and/or combinations of filters are implemented on the image. In addition, by focusing on the light spectrum between 580-660nm, and neglecting spectrums outside that range, key areas of interest are able to be highlighted. The post-processed image is then passed through the corrosion detection algorithm where the rust pixels are identified (Figure 2). The rust pixels are identified using the hue, saturation, and value (HSV) where the values used to identify pixels if they all fall in the range of 0-20° for hue, 70-200 for saturation, and 70-150 for value.

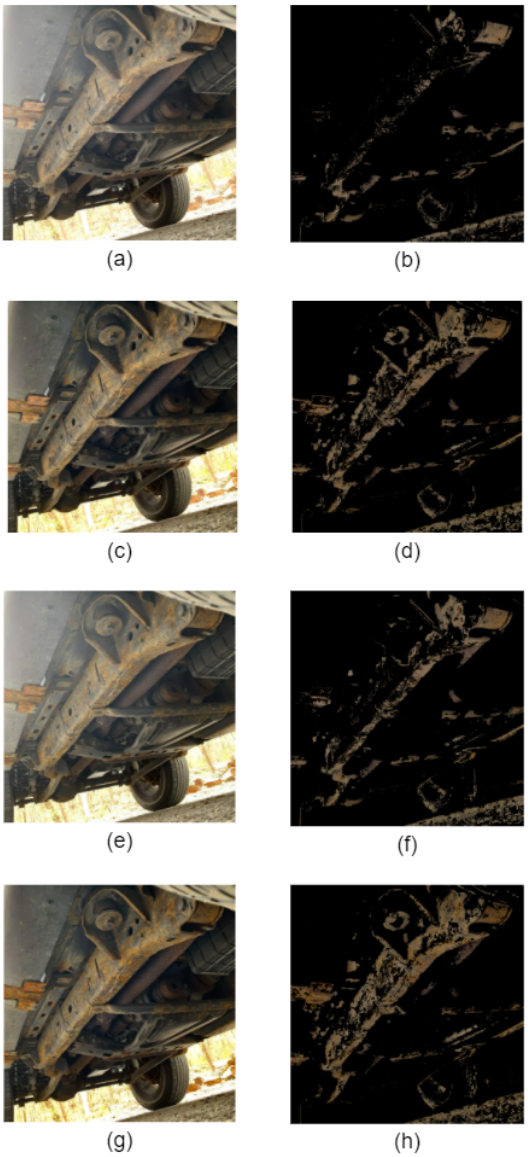


Figure 2: Rust detection algorithm results comparing the raw image and its rust detection output mask, versus filtered images and their rust detection output mask. (a) and (b) are the raw image, (c) and (d) utilizes the dehaze 75 filter, (e) and (f) utilizes luminance -100, and (g) and (h) are the combination of the dehaze 75 and lumination -100 filters

[1] https://photoeditor.polarr.co/

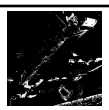
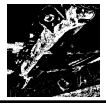
Measured Value of Rust in Pixels					
Rust Detection Masks	Binary Image	Precision of Detected Rust Pixels	Recall of Detected Rust Pixels	F1-Score of Detected Rust Pixels	Total Corroded Pixels
Ground Truth		-	-	-	198117
Raw Image (Control)		0.63	0.22	0.33	69258
Filter 1: Luminance -100		0.65	0.35	.45	107225
Filter 2: Dehaze 75		0.63	0.45	0.53	141888
Filter 3: Luminance -100 Dehaze 75		0.61	0.51	0.55	160046
Filter 4: Vibe -25, Dehaze 75, Highlight -100, lum -100		0.63	0.57	0.60	178484

Table 1: Shows a sample of the resulting values of Precision, Recall, and F1-Score in regards to corroded / white pixels on a set of four images. The listed images include a control image with no filter, an image filtered on with -100 Luminance of pixels containing wavelengths 580 - 660 nm (Filter 1), an image filtered with Dehaze 75 (Filter 2), and an image containing the combination of both filters (Filter 3).

3 EXPERIMENTS AND RESULTS

The corroded undercarriage of a vehicle was imaged using an iPhone 10s's camera and post-processed with nine varying image filters for input into the corrosion detection algorithm. The goal being to determine which combination of methods yields the highest level of detection accuracy, with respect to the ground truth image. The algorithm's performance, being its ability to identify corroded pixels, was quantified utilizing an F1 score, precision, and recall which can be seen in equations (1), (2), and (3).

$$Recall = \frac{TP}{TP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$F1 = 2 \bullet \frac{precision \bullet recall}{precision + recall} = \frac{TP}{TP + \frac{(FP+FN)}{2}} \quad (3)$$

The F1 score is calculated as a harmonic mean between detection recall and precision. Quantification of the image processing technique's performance, as a function of precision, recall, F1 score, and the number of identified corrosion pixels, is shown in Table 1. In some cases a large increase in rust pixel count was shown with either a decrease or very slight increase in F1 score. This result indicated the occurrence of a high number of false positives and false negatives to lower both the recall and precision of the image. It was demonstrated that by combining four filters at selected scales (vibrance -25, dehase +75, highlight -100, luminance -100) we yielded an increase from the raw image F1 score of 0.33 to a new F1 score of 0.60 showing our highest improvement.

The highest performing individual filter was dehaze. Dehaze improved contrast in the photo across low frequency areas in the image. Low frequency areas are those in which the mean pixel value is changing slowly over time causing a haze in the image. Luminance, another well performing individual filter, combined with dehaze produced the best performing combination between two filters. Luminance is the intensity of light emitted from a

surface per unit area in a given direction. Reducing luminance of rust specific wavelengths of light, 580-660nm, removes noise from brightness while keeping the color of those pixels. Dehaze and luminance worked together to remove unnecessary haze due to brightness and more clearly establish rust pixels.

4 CONCLUSION

In this paper, we show that through a series of image post-processing techniques the detection of rust in an image can be improved from an F1 score of 0.33 to 0.60. The techniques and filters presented above, while by no means are the only ones usable, prove to be beneficial in the evaluation of rust in an image. Moving forward in our research we will look into increasing our data set with more images of greater variability in quantity and types of rust, along with quality of images.

In effort to further improve our rust detection algorithm we have begun investigating and testing secondary methods of verification and identification of rust. These include and are not limited to the utilization of texture analysis using edge detection technology and gray level co-matrices.

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