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CHARACTERIZATION OF CORROSION PRODUCTS ON CARBON STEEL USING HYPERSPECTRAL IMAGING IN SHORT-WAVE INFRARED (SWIR)

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ABSTRACT

Corrosion can cause major damage to steel structures and if not monitored and controlled in time, it can result in complete failure of these structures. In situ corrosion monitoring has been challenging as most in-situ techniques require direct contact to the structures, are time consuming and risky. Hyperspectral (HS) cameras can help detecting surface chemical changes by collecting reflectance information outside the visible part of the electromagnetic spectrum. In recent years, low-weight, low-cost HS cameras have been developed that can be mounted on drones or robots for in-situ inspection. The aim of this study is to evaluate the potential of hyperspectral data in the Shortwave Infrared (SWIR, 1100-1700 nm) range for corrosion detection and characterization. For that, steel samples were immersed in water for different periods of time, resulting in the occurrence of different degrees and types of corrosion. The results demonstrate the potential of hyperspectral data in the SWIR range for the detection of different degrees and types of corrosion.

Index Terms— Corrosion, Hyperspectral imaging, Non-destructive testing, Material characterization, Chemical analysis

1. INTRODUCTION

Corrosion is one of the most common damages to metal structures. As corrosion increases on metal, it can reduce the thickness of metal which can lead to fatigue cracks and buckling and eventually the failure of the entire metal structure. NACE International, the global corrosion authority estimates that the worldwide cost of corrosion is \$2.5 trillion per year. A recent study of 2016 (http://impact.nace.org) states that implementing corrosion prevention can lead to global savings of between 15-35% in damage costs.

In recent years, imaging techniques have been introduced as fast, inexpensive and safe methods for in situ monitoring of large structures and to detect the color, morphological, roughness and textural changes on the surface caused by anomalies such as coating delamination and corrosion [1-4]. The main limiting factor of RGB cameras is the narrow spectral range. In addition, the detection of corrosion with RGB cameras is known to be prone to false positives and features like bird droppings or microbial growth are often misclassified as corrosion.

Hyperspectral imaging (HSI) is an imaging technology that collects light reflected from a target surface in hundreds of very narrow and contiguous spectral bands to provide a near-continuous reflectance spectrum for each pixel in the image. The HS cameras can work in the near and shortwave infrared (700-2500 nm) wavelength ranges, for which different minerals exhibit different spectral behavior. If explored more, HIS can distinguish between corrosion and other artefacts and distinguish between different types of corrosion.

So far, there has not been much reported research on the use of HSI for corrosion monitoring. A recent report by a hyperspectral sensor manufacturer [5] demonstrated the advantage of using the SWIR spectral range for the analysis of different degrees of corrosion. In another report, HSI was identified as technologically suitable for corrosion inspection by drones [6]. In [7], hyperspectral SWIR data was applied to a cultural heritage application, i.e. the characterization of corrosion on bronze sculptures. In this study, specific absorption characteristics of in-situ hyperspectral measurements of a sculpture were related to laboratory spectral measurements of two common bronze corrosion products, Brochantite and Antlerite.

Despite the potential of HSI for corrosion inspection, few qualitative studies have been conducted on this topic and the spectral behavior of different corrosion types with different chemical compositions has only recently been investigated [8]. In that study, the presence of different corrosion minerals on corroded steel samples (prepared in a salt spray corrosion accelerating chamber) was estimated using a Specim FX17 camera (900-1700nm). It was acknowledged that the presence of mixtures of different iron oxides makes corrosion inspection challenging and requires high quality spectral information beyond the visual range and robust analysis techniques.

In this study, we will compare the spectral behavior of different corrosions on carbon steel samples immersed in water for different times. Different corrosion types appear on both immersed and non-immersed areas of the samples. The samples were then scanned in a controlled laboratory environment with an Imec Snapscan hyperspectral camera in the SWIR range (1100-1650nm). The result of the

spectral analysis was validated with ground truth chemical compositions of the corrosions, obtained by Scanning Electron Microscopy with Energy Dispersive X-Ray (SEM-EDX).

2. MATERIALS AND METHODS

In this study, 5 carbon steel samples were immersed in water (5 wt% CaCl₂) for different durations from 2 hours, to 1, 3, 6, and 11 days. The submerged zone and atmospheric zone (outside water) of the samples are shown in Figure 1 with selected regions for SEM-EDX analysis. These regions are selected based on their locations and appearance on the samples; Rec1 is selected rectangle from the submerged zone of the samples where a uniform corrosion layer is formed, Rec2 is selected on the reddish boundary line between the submerged and the atmospheric zones (directly above the submerged zone), Rec3 is selected on the greenish boundary line closer to the atmospheric zone, Rec4 is selected in the blank steel region (without corrosion), Arrow1 and Arrow2 denote yellowish and dark corrosion spots in the atmospheric zones respectively. It should be noted that the SEM-EDX analysis has only been conducted on samples of Day 3, Day 6, and Day 11. However, hyperspectral images are taken from all the samples (RGB image of all samples are shown in Figure 2). Because there was a time difference between the SEM analysis and hyperspectral scanning (HS scanning was performed 2 weeks after SEM analysis) more corrosions -had grown on the surface of the samples at the time of HS scanning (Day11 in Fig.1 vs. Day 11 in Fig.2).



Figure 1. Selected regions for SEM-EDX analysis

The samples were then scanned with SnapScan hyperspectral cameras in SWIR range(1100-1700nm) manufactured by Imec team. Despite conventional hyperspectral cameras with line-scanner sensors, SnapScan cameras do not require moving or translating stage. Instead, the sensor moves inside the camera to provide images from different wavelengths frame by frame. Moreover, due to having compact sizes and low weights these cameras can be mounted on drones or robots for in-situ scanning. More specifications of the camera is given in Table1. The Imec SWIR camera used in this study is lent by Engie Laborelec to the University of Antwerp for research.

Table 1. Specifications of the hyperspectral camera

Spatial resolution (pixels)	1200×640
Spectral resolution (bands)	113
Spectral range	1100-1650 nm
SNR	up to 600:1
Dimensions, Weight	9×9×15 cm, 895 gr

This experiment was conducted under controlled laboratory condition. To control the ambient light, the laboratory room is made dark and 4 halogens lights (20W) with diffusors were used as illumination source. The camera was located vertically on top of the samples with a distance of approximately 30cm. An adjustable metal rack is used to fix the distance of the samples to the camera. The irradiance raw images were calibrated and converted to reflectance images after scanning a white reflectance panel with 95% reflectance and using the camera acquisition software.



Figure 2. RGB images of steel samples at the time of HS scanning

3. SPECTRAL ANALYSIS AND CLASSIFICATION

After scanning the samples, the spectra of the different regions (determined in section 2) were averaged and plotted in raw reflectance mode. The averaged spectra were then normalized by dividing each spectrum by its norm. Normalizations take a vector of any length, preserving its direction, but changes its length to 1. This pretreatment minimizes the scaling effects in the spectra due to different illumination angles and only looks at the direction of the spectra. For better visualizing of the absorption features in the spectra, the overall concave shape of a spectrum is removed. This pretreatment is called 'continuum removal' or 'convex-hull' transformation and allows comparison of the absorption features of the spectra [9]. After normalization and continuum removal pretreatment the spectra of different regions on the samples are compared. The image data from the Day11 sample (with high corrosion) was then used for classification. The goal here is to categorize all pixel spectra on the surface and assign them to one of the 6 regions defined in Section 2. The classifier

we used in this study is a Support Vector Machine (SVM). A basic SVM separates the spectra by hyperplanes, positioned at the maximal margins between the spectra of 2 classes that are closest to each other (support vectors). Kernelization extends the method to nonlinear decision boundaries [10].

4. RESULTS

4.1. SEM analysis results

The chemical analysis results of SEM-EDX are summarized in Table 2. This analysis was performed by experts from Engie Laborelec in Belgium. The results from Table 2 show that with longer immersion time, the amount of oxygen in corroded areas increases and conversely, the amount of Fe decreases. This increase in the amount of oxygen and decrease in Fe is also observed, going from Rec1 to Rec2 and Rec3, as more iron oxide is formed in the boundary lines of the samples compared to the part that was entirely submerged in water. Additionally, at the boundary between submerged and atmospheric areas (Rec2 and Rec3), some amount of Ca and Si was observed, which increases with longer immersion time. In Arrow1 and Arrow2, Cl appears. Note that Arrow 1 did not appear in sample Day6.

	Elements	0	Na	Mg	Si	Cl	Ca	Cr	Mn	Fe	Ni	Cu
Day 3	Rectangle1	2.57	0.20	0.00	0.24	0.11	0.00	0.32	0.43	95.27	0.21	0.66
	Rectangle2	10.18	0.23	0.14	2.29	0.00	0.10	0.32	0.50	85.77	0.00	0.47
	Rectangle3	17.23	0.46	2.78	1.55	0.00	19.01	0.11	0.51	58.35	0.00	0.00
	Rectangle4	0.65	0.00	0.00	0.12	0.00	0.00	0.14	0.54	98.37	0.00	0.18
	Arrow1 (1)	20.53	0.21	0.00	0.21	6.04	0.00	0.00	0.00	73.01	0.00	0.00
	Arrow2(1)	20.60	2.20	0.00	0.34	0.19	0.16	0.00	0.26	76.25	0.00	0.00
	Arrow2(2)	13.94	0.42	0.00	0.17	0.28	0.07	0.11	0.43	84.59	0.00	0.00
Day 6	Rectangle1	3.56	0.28	0.12	0.19	0.00	0.00	0.50	0.59	93.50	0.00	1.00
	Rectangle2	20.99	0.39	0.18	3.38	0.15	15.96	0.18	0.45	57.85	0.00	0.27
	Rectangle3	22.21	0.48	0.82	0.50	0.08	33.94	0.15	0.56	41.09	0.00	0.00
	Rectangle4	0.85	0.00	0.00	0.17	0.00	0.00	0.18	0.55	98.07	0.00	0.18
	Arrow2 (1)	17.09	0.44	0.00	0.13	0.09	0.00	0.00	0.49	81.76	0.00	0.00
	Arrow2 (2)	1.24	0.21	0.00	0.11	0.00	0.08	0.18	0.46	97.52	0.00	0.19
	Rectangle1	8.55	0.00	0.14	0.40	0.13	0.00	0.95	0.56	86.85	0.14	1.55
	Rectangle2	16.09	0.00	0.19	4.33	0.14	1.80	0.14	0.61	76.51	0.19	0.00
	Rectangle3	28.61	0.66	0.77	0.28	0.46	34.64	0.00	0.45	34.01	0.00	0.00
	Rectangle4(1)	0.98	0.19	0.00	0.09	0.00	0.00	0.17	0.45	98.11	0.00	0.00
Day 11	Rectangle4(2)	19.29	2.25	0.00	0.97	0.64	0.50	0.00	0.85	75.28	0.00	0.00
	Arrow1(1)	16.31	0.00	0.00	0.14	9.71	0.00	0.00	0.13	73.70	0.00	0.00
	Arrow1(2)	12.80	1.84	0.00	0.08	0.89	0.00	0.09	0.44	83.85	0.00	0.00
	Arrow2(1)	21.68	3.83	0.00	0.18	0.24	0.37	0.00	0.62	73.08	0.00	0.00
	Arrow2(2)	23.81	0.00	0.00	0.00	7.10	0.00	0.00	0.00	69.09	0.00	0.00
	Arrow2(3)	10.91	0.70	0.00	0.00	0.24	0.00	0.00	0.46	87 41	0.00	0.00

Table 2. SEM chemical analysis of different regions

4.2. Spectral comparison

The spectra of Rec1 and Rec2 increase in reflectance values with increasing immersion time, in the entire wavelength range. However, in Rec1 and Rec2, a gradual increase in reflectance values is observed after 1,400 nm and after 1,370 nm, respectively, which is more apparent in samples with longer immersion time (Fig.3-1a and Fig.3-2 a). A similar pattern is observed in normalized spectra when samples are longer immersed in water in both Rec1 and Rec2 regions (Fig.3-1b and Fig.3-2b). However, the normalized spectra of Rec3 do not change with increasing

immersion time (Fig.3-3b). When continuum removal (CR) pretreatment is applied to the spectra, two absorption features around 1,200 nm and 1,500 nm are observed in Rec1, Rec2, and Rec3 (Fig.3.1c, Fig.3.2c, Fig.3.3c). The size of the absorption features at 1,500 nm reduces with increasing immersion time, except in Rec3.

As with corrosion in the immersed zone, the reflectance values of corrosions in the atmospheric zone; in Arrow1 and Arrow2, also increase with immersion time, except at Arrow2 of Day11 (Fig.3-4a and Fig.3-5a). However, this is merely a scaling effect because after normalization, the spectrum of Arrow2 in Day11 becomes closer to the spectra of Day3 and Day6 (Fig.3-5b). The average spectrum of Arrow1 in Day11 contains an absorption feature at 1470 nm (Fig.3-4a). This feature was not observed as clearly in the average spectra of other regions and it is relatively large when plotting the CR spectra (Fig.3-4c).



Figure 3. Spectral behavior of different regions in the SWIR range

In Fig. 4, the average, normalized and continuum removed spectra of the 6 different regions in sample Day11 are plotted against each other. The normalized spectra of different regions are distinctive, except for the spectra of

Rec3 and Arrow2 which are very similar (Fig.4a). The CR spectra are also quite distinctive (Fig.4b).



Figure 4. Spectral behavior of different regions in sample Day11

4.3. Classification results

Each of the regions in Sample Day11 (Rec1, Rec2, Rec3, Rec4, Arrow1, and Arrow2) is considered as a different material class. A SVM classification model was built using one third of the pixels in each region as training data and keeping the other two third for testing. The model was then applied to the entire sample Day11 (Fig.5). Because full-surface ground truth was not available, the classification results on the sample were only assessed qualitatively. In the submerged zone, the different corrosion classes (Rec1, Rec2, Rec3) are quite well distinguishable (Fig.5b). The SWIR image leads to good classification results for Arrow 1, Arrow2 and Rec4 in the atmospheric zone as well.



Rec4 Arrow1 Arrow2

Figure 5. RGB image and SVM classification map of sample Day11

5. CONCLUSIONS

In this study, different corrosion products on steel with different chemical compositions were studied using hyperspectral data in the SWIR range (1100-1650nm). The results showed that as Fe decreases and oxygen elements increase (i.e., corrosion increases), the spectral behavior of corrosion products changes as well. Also, the appearance of other chemical elements in the corrosion products changes their spectral behavior. Therefore, the potential of hyperspectral imaging technology is demonstrated not only for detecting corrosion, but also for characterizing different types of corrosion with different chemical compositions. The results also showed that different types of corrosion can be classified and segmented in a HSI. More detailed studies are needed to accurately distinguish different corrosion products with HSI data. In the next phase of this study, hyperspectral mineral maps will be compared with XRD ground truth, which is more useful for mineral and phase detection.

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