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Reflectance Transformation Imaging (RTI) data analysis for change detection. Application to monitoring protective coating failure on low carbon steel.

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Abstract

This paper examines two new methodological approaches exploring Reflectance Transformation Imaging (RTI) data processing for detecting, documenting, and tracking surface changes. The first approach is unsupervised and applies per-pixel calculations on the raw image stack to extract information related to specific surface attributes (angular reflectance, micro-geometry). The second method proposes a supervised segmentation approach that, based on machine learning algorithms, uses coefficients of a fitting model to separate the surface's characteristics and assign them to a class. Both methodologies were applied to monitor coating failure, in the form of filiform corrosion, on low carbon steel test samples, mimicking treated historical metal objects' surfaces. The results demonstrate the feasibility of creating accurate cartographies that depict the surface characteristics and their location. Additionally, they provide a qualitative evaluation of corrosion progression that allows tracking and monitoring changes on challenging surfaces.

Introduction

Tangible cultural heritage (CH) preservation aims to stabilize the object's condition and ensure its safeguarding for future generations. For metal cultural heritage artifacts, the main cause of deterioration is corrosion. Corrosion is the continuous process of the metal's interaction with its environment and the subsequent effect on its chemical structure. In visual observations, corrosion manifests through changes in the color and texture of the surface. In conservation-restoration treatments, the most common preventive measure for its limitation is the application of a protective coating. However, coatings do not indeterminately prevent corrosion progression and can exhibit coating failure. To detect and control this ongoing process, monitoring is performed. In museum collections, this usually corresponds to measuring the environmental conditions and not the objects' surface changes.

In this paper, monitoring is examined regarding surface change detection on low-carbon steel by implementing Reflectance Transformation Imaging (RTI). Two complementary methodologies for processing RTI image data are examined. The particular interest is to detect, characterize and track the failure of protective coating systems on these surfaces. The paper structure is as follows (i) background information on the coating failure and the selected technique (ii) Description of the methodology and selection of the cases to be applied; (iii) application of the methodology for monitoring coating failure; (iv) data interpretation; and (v) conclusions.

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Background

Filiform corrosion is a particular form of localized corrosion encountered on painted or varnished metals. It usually appears on ferrous or aluminum alloys coated with organic paints or varnishes and is related to coating failure. The characteristic of this form is the creation of filaments that develop under the coating that occasionally develops over the coating layer. Numerous references in the literature exist on the corrosion mechanism and its effect, with particular interest in industrial metals [1–4]. In cultural heritage, the relevant references are limited and mainly related to the failure of transparent coatings to protect iron artifacts during the conservation process [5–7]. In these occurrences, corrosion initiates at areas of preexisting localized corrosion on objects that retain the metal core. This corrosion phenomenon creates changes in the surface appearance that manifest as localized changes in color and micro-topography.

Figure 1 demonstrates these surface changes and their relevant size. The fine-scale of this corrosion phenomenon complicates evaluating and documenting these surface anomalies by visual analysis. Microscopic observation can make it possible to evaluate the surface condition; however, monitoring and tracking changes is very time-consuming, and the evaluation through visual observations is a subjective methodology based on expertise.

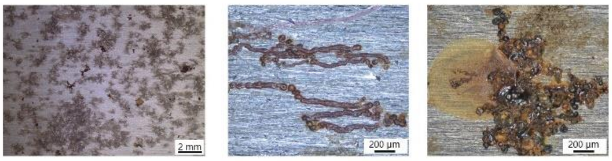

Figure 1. *Examples of coating failure leading to filiform corrosion. Left: General appearance of an iron surface with random spots of filiform corrosion (stereoscopic view). Middle: Corrosion filament below the coating (Dark field optical microscopy). Right: Extensive coating failure and corrosion over the coating (Dark field optical microscopy)*

RTI for assessing CH metal surfaces

RTI (Reflectance Transformation Imaging) is a Multi-light Image Collection (MLIC) technique that creates an image stack of stationary viewpoints under different lighting angles. In RTI acquisitions, the object is positioned orthogonal to the camera, and a series of images are acquired from different illumination positions at a fixed distance. This results in an exploitable RTI image stack that can be used for further data processing and analysis (Fig.2).

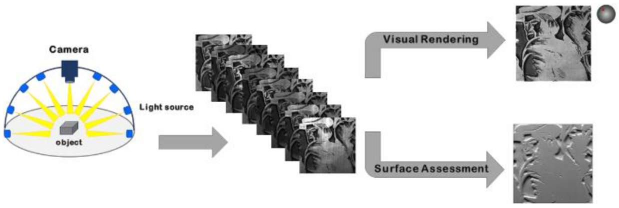

Figure 2. *RTI principle for capture and data analysis.*

RTI has been introduced in cultural heritage applications as a portable, easy-to-use, non-invasive, image-based technique for studying surface textures [8]. It is, to date, mainly used to study the artistic and technological characteristics of objects or artworks [9-12]. RTI has also been explored as a scientific tool in the past decade. Different perspectives have been examined for documenting not only object surfaces but also conservation treatments [13–18] or for revealing underlying information with the integrated use of spectral imaging [15,19] and to map defects with clear topographic changes [20, 21]. However, little research exists for documenting metal surfaces [22] or monitoring metal conservation treatments [13,17, 18].

These papers focus on the ability to enhance details by examining relighting and enhanced surface visualization. RTI as a visual inspection tool for failure analysis was also explored by Coules *et al.* (2019) [22] for examining industrial metal surfaces. In terms of the application of RTI as a tool for change detection, the literature was limited to case study-oriented methodologies, most of which compare relightable images [14–18]. The first to introduce a different methodology for measuring changes using RTI was Manfredi *et al.* (2014) [20], which created damage maps comparing the directional changes of the surface normal before and after damage. Later, in 2020, Corregidor *et al.* [21] introduced an image-processing methodology combining RTI specular enhancement and edge detection algorithms to isolate and document topographic defects (i.e., scratches) on similar coins.

Herein two novel approaches in RTI data processing for cultural heritage surfaces are examined [23, 24], providing complementary information with a particular interest in detecting, characterizing, and tracking the failure of protective coating systems on metal surfaces. The proposed methodologies can lead the way to automated condition documentation of challenging surfaces objectively. Nevertheless, the validity of the results is based on expert evaluation since establishing a ground truth for such a surface is complicated.

Materials and methods

Materials

Filiform corrosion is a long process, and to study it promptly, artificially corroded test plates (coupons), made of low-carbon steel, and presenting different degrees of filiform corrosion were produced (Fig. 3). Coupon preparation was based on past protocols [5, 7] on the following steps:

- Step 0: Low carbon steel coupons (DC 04 EC 10130:2006). Metal test plates with dimensions 4x5x0.2cm were used. The composition per manufacturer was Fe >99%, with carbon percentage C 0.033% and traces of Si, P, S, and Al.
- Step 1: Initial corrosion. Coupons were corroded under varying relative humidity (RH) and temperature (T) until the surface was covered with localized corrosion spots. These spots are randomly dispersed over the surface while the metal stays intact in other areas.
- Step 2: Surface cleaning. Coupons were mechanically cleaned to remove only friable corrosion products based on conservation-restoration methodologies. After cleaning, the surface exhibits corrosion spots at the same level as the metal surface.
- Step 3: Coating. After cleaning, they were degreased and coated with Paraloid B72 (an ethyl methacrylate and methyl acrylate copolymer) 15% w/v in acetone. The coating was applied by brush, following standard conservation practices. Two layers with perpendicular directions were applied.
- Step 4: Accelerated corrosion. The coated test plates were again corroded under varying RH & T until coating failure and signs of filiform corrosion were visible. Coupons were removed at different time intervals to obtain a series of specimens with varying levels of corrosion (Fig. 4).

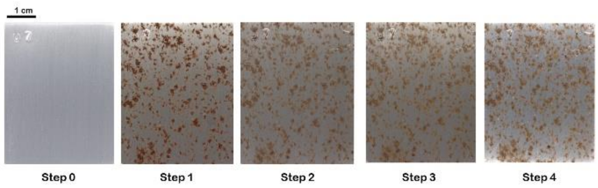

Figure 3. *Photographic documentation of the coupons preparations steps*

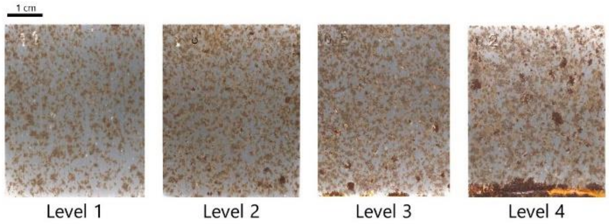

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Figure 4. *Artificially corroded low carbon steel test plates presenting different degrees of filiform corrosion. From left to right the corrosion spots become more visible.*

Methodologies

Two different RTI data processing approaches are presented for tracking changes on artificially corroded surfaces. The first method is based on feature analysis of the per-pixel angular surface reflectance. This methodology allows extracting accurate cartographies of the surface's properties and evaluating the local surface's saliency from these cartographies [23, 25]. The second method proposes a supervised segmentation, based on machine learning algorithms, that creates user-defined classifications through the HSH (Hemi-Spherical Harmonics) coefficients of RTI fitting models [24].

Capturing system

Monitoring with RTI requires a system with reproducibility and repeatability in terms of acquisition. Therefore, an automated RTI system is preferable. A custom-made dome was used, equipped with a single light source (cold white LED, 5000 K) and an industrial, monochromatic camera with a CMOS sensor (Sony IMX304, resolution 4112(H) × 3008 (V)). Coupon positioning and distribution of the lighting angles were the same for each acquisition. This system is equipped with a user interface that allows controlling the acquisition parameters and creates accurate and repeatable acquisitions. A complete system description is provided in [25].

Due to the high specularity of the surface, instead of using a single exposure time, the full dynamic range of the response of the surface was measured using Hight Dynamic Reflectance Transformation Imaging (HD-RTI) [27].

Feature analysis

The first approach is unsupervised and applies per-pixel calculations on the raw image stack to extract information on specific surface features. They correspond to the per-pixel analysis of the image stack, and they result in a single visualization cartography (feature map). These maps can provide information on the response of each pixel of the surfaces in relation to the selected feature in a global way. The corresponding workflow is shown in Figure 5.

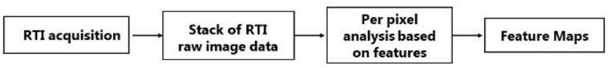

Figure 5. *Method 1: Workflow for feature analysis.*

Following the proposed workflow, information is extracted from the raw RTI data and is related to the geometry or the reflectance response of the imaged surface. Geometric features are related to the surface's directional, curvature, or angular characteristics depicted through their normal, slopes and curvatures. Therefore, they can give information associated with manufacturing techniques, decorative characteristics (e.g., tool marks), surface defects (e.g., cracks), or corrosion processes (e.g., development of oxides) that provoke changes to the surface's topography. On the other hand, statistical features provide information related to the angular reflectance response of the surface; thus, are highly affected by appearance attributes like color, gloss, or texture. In addition, statistical features can easily depict changes related to surface specularity or light absorption. There are numerous feature possibilities [23, 25]. However, here only the ones that are related to the particular study are presented, namely the mean (eq.1) and the Shannon entropy (eq.2) from the statistical features, and the directional maps Dx (eq.3), Dy (eq.4), and the curvedness (eq.5) from the geometric features.

In detail, for an RTI acquisition of N images**,** each surface pixel is associated with an N size vector corresponding to the local angular luminance ($L_{i,j,k}$). Then, depending on the selected feature, the corresponding algorithm is applied to the N images for each pixel position X=L(i, j, k), where i and j are the pixel's coordinates and k the image number in the stack.

The mean feature (Eq.1) calculates the average reflectance response of each pixel and therefore provides a general description of the surface's appearance.

$$\boldsymbol{\mu = \frac{1}{N}\sum_{k=1}^{N} X_k} \quad \textit{Eq. 1}$$

The Shannon entropy measures the "chaos" in the distribution of the pixels for the different reflectance responses per light position (Eq.2). High values indicate that pixel distribution is more random. The interpretation of the visualized result is case-dependent.

$$\mathbf{H = -\sum_{k=1}^{N} P\,(X_k)\log^2 P\,(X_k)} \quad \textit{Eq. 2}$$

where P the probability of X

Geometric features are calculated from the surface normals ($\vec{N}$) based on photometric stereo models. Then N_x, N_y, N_z are the directional components of the X, Y, Z cartesian coordinates. Accordigly, the Dx (Eq.3) and Dy (Eq.4) are the directional slopes of the X and Y axis, where Px/y size is the pixel size (in mm) over the respective axis (X/Y). These features are affected by the surface rotation and describe characteristics related to or affected by surface directionality.

$$\mathrm{D_x} = P_{\mathrm{size}}^{\mathrm{x}} \frac{\overrightarrow{\mathrm{N_x}}}{\overrightarrow{\mathrm{N_z}}} \quad \textit{Eq. 3}$$

$$\mathrm{D_y} = P_{\mathrm{size}}^{\mathrm{x}} \frac{\overrightarrow{\mathrm{N_y}}}{\overrightarrow{\mathrm{N_z}}} \quad \textit{Eq. 4}$$

The curvedness (Kc) (Eq.5) expresses the degree of the surface's curvature and is calculated based on the Kmin, and KMax where Kmin and KMax are the principal curvatures of a set of normal curvatures [24]. This feature is invariant to surface rotation and better describes the texture of a surface.

$$\mathrm{K_c} = \sqrt{\frac{\mathrm{K_{min}^2} + \mathrm{K_{Max}^2}}{2}} \quad \textit{Eq. 5}$$

Despite the complexity of the calculations, the application is straightforward, as described in the workflow presented in figure 5.

Segmentation

The second method proposes a supervised segmentation approach that uses the coefficients of the Hemispherical

Harmonics (HSH) fitting model to match similarities of the surface characteristics and assign them to a class. In RTI, fitting models are used for visualizing the surface-based reconstruction models for the acquired light positions. These light positions represent the per-pixel reflectance in the different lighting directions. The most commonly used models are Polynomial Texture Mapping (PTM) and Hemi-Spherical Harmonics (HSH), which are based on the use of coefficients with fixed numbers 6 and 16, respectively. HSH was selected to provide more accurate information than PTM in the case of specular surfaces. A novel data processing workflow for the segmentation and classification of RTI data was adapted based on exploiting these coefficients through a linear discriminant analysis model (Fig. 6) [24].

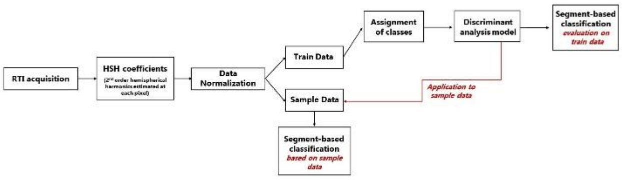

***Figure 6**. Method 2: Workflow for RTI data segmentation.*

The method proposes a supervised approach for the automated condition documentation and surface monitoring of metal surfaces by applying classification through segmentation. Using the RTI image stacks, HSH coefficients are utilized to create discriminant models, based on each supervised class (C), to predict the surface appearance over time. The discriminant model is created based on Fisher's [28] multiclass separation model (Eq.6) for creating the trained data. This model is then applied to evaluate the other surfaces (sample data). It is assumed that each of C classes has a mean μ_i and the same covariance Σ. Then the scatter between class variability may be defined by the sample covariance the of class means μ.

$$\Sigma_b = \frac{1}{C}\sum_{i=1}^{C}(\boldsymbol{\mu}_i - \boldsymbol{\mu})\,(\boldsymbol{\mu}_i - \boldsymbol{\mu})^T \quad \textit{Eq. 6}$$

After segmentation, each detected category is assigned to a single class, and results are presented with colormap visualization. It needs to be noted that since the method is supervised and user-dependent therefore, the information to be segmented must be carefully selected based on the research question.

Results and Discussion

Figure 4 shows the series of coupons exhibiting four degrees of accelerated aging. For the RTI acquisitions, a region of interest in the center of the coupons was selected (covering an area of around 1.2x2cm). This allows for global observation of the surface while avoiding misinterpretations due to the edge effect visible on the bottom of the coupons at levels 3 and 4. The resulting information is evaluated based on expertise and repeatability of the methodology in similar case studies [23, 24].

Feature analysis

The most important appearance characteristic of filiform corrosion is the creation of filaments that start under the coating but, as the corrosion propagates, can extend over the coating. This creates local anomalies that visibly change the surface color and micro-geometry.

Figure 5 presents the most relevant feature maps for the different levels of corrosion. The mean map represents the average reflectance response of each pixel and therefore shows the average appearance of the surface. Since the coating is transparent, it is difficult to distinguish the areas where it started failing or if filaments have developed over the coated surface. Geometric maps can characterize in detail the surface topography. Having been applied by brush, the coating has a specific directionality, and in the Dy map, the coating directionality becomes minimal, allowing better observation of what is happening on top of the coating surface. The areas where the corrosion products have extended over the coating and their location are depicted. The curvedness map indicates the curvature of the surface. In this specific case, the corrosion that has exceeded the coating, changes the curvature properties of the coated surface. The Dy and curvedness map shows the corrosion propagation between the different levels. For level 1, filiform corrosion is developing underneath the coating in contrast to levels 2-4. However, when observing levels 2-3, it is difficult to determine where the extent of corrosion is greater. This is resolved through the segment-based classification methodology. However, for the coating itself, the geometric alteration is less prominent for the geometric maps to detect changes. This is visible through the Entropy that indicates coating failure based on higher randomness values.

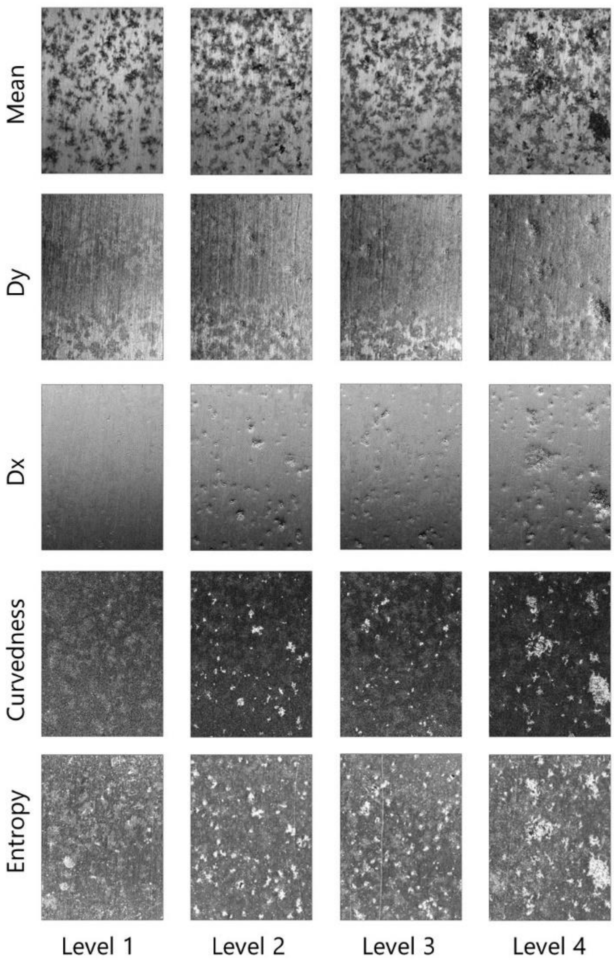

***Figure 5**. Feature maps analysis on coating failure and penetration of the corrosion products over the coating*

Segmentation

The segmentation method explores information related to the reflectance response of the surface by assigning areas to classes having similarities in their appearance. In this case, two classes were defined by the cultural heritage expert: (a) the coated area marked in yellow and (b) the corrosion that was visible over the coating marked in blue. Then, the method analyzed the surfaces and created cartographies that depict the areas where the two classes appear. In parallel, a semi-quantitative evaluation is possible by counting the percentage of pixels of a class in each corrosion level. Fig.6 shows the maps of the ROIs segmented in the two supervised classes. The different surfaces present various extents of corrosion, as indicated in levels 1 to 4. Therefore, quantifying the percentage of detected corrosion gives a clear indication of the extent of the corrosion penetration of the coating. In addition, it helps separate what is visibly difficult between level 2 and level 3.

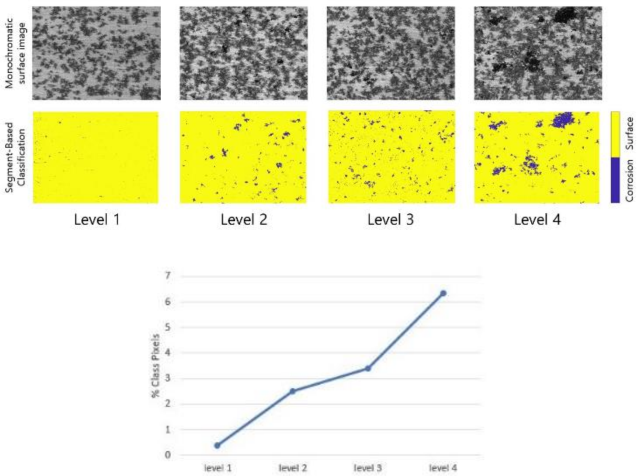

***Figure 6**. Segmentation of corrosion products penetrating the coating at different corrosion levels and qualitative analysis of the extend of corrosion on the metal surface.*

Conclusions

This paper proposes a new change detection methodology based on processing RTI data and its application to study coating failure on metal substrates. The two methods examined demonstrate the feasibility of detecting, recording and evaluating the surface changes due to corrosion on high specular surfaces. They provide accurate, automated cartographies of the surface's condition. In addition, they give complementary information and help assess the corrosion progression while producing cartographies of where these changes are happening and to what extent. Feature analysis serves in the accurate understanding of the surface's textural and reflectance characteristics. The changes on the surface at different levels are well depicted, while an indication of coating failure is possible. The segmentation is based mainly on the surface's geometric features. Using coefficients to determine change provides less detail in characterizing the surface. However, it helps easily segment user-defined surface characteristics with similar reflectance behavior and depict their position. Furthermore, calculating the percentage of the segmented information produces a clear trend of the propagation of change possible.

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