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Appearance Segmentation and Documentation Applied to Cultural Heritage Surfaces

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Abstract

This paper describes the application of a novel supervised segmentation technique used for conservation documentation based on visible appearance changes of Cultural Heritage (CH) metal surfaces. The technique employs a linear discriminant analysis model to classify Reflectance Transformation Imaging (RTI) reconstruction coefficients. The Hemispherical Harmonics (HSH) reconstruction coefficients for each pixel are first calculated and then normalized. This normalization enhances the robustness and invariance of the application, making it possible to apply it for documenting different surfaces at different time intervals. This paper presents three cases related to surface appearance changes due to corrosion that provokes low or high topographic changes. Tarnishing of silver and filiform corrosion on steel are examined. For each case study, a supervised data set is constructed, teaching the algorithm to recognize as distinct a specified appearance characteristic (such as corrosion, metal, etc.) by comparing it to the reconstruction coefficients of each pixel through Linear Discriminant Analysis (LDA). A simplified color map visualizes the segmented information. The calculated results are afterward verified by visible inspection from conservation-restoration experts. The method can segment surfaces with changes in micro-geometry, creating accurate cartographies of the object's condition. However, limitations are met on surfaces with minimal topography and high specularity.

Keywords: RTI -Reflectance Transformation Imaging, Hemispherical harmonics, Normalization, Linear discriminant model, Appearance segmentation, Visualization, Conservation documentation, Condition assessment

Introduction

The use of imaging tools, as well as their subsequent processing and analysis, is crucial for providing a visual record of conservation processes. Reflectance Transformation Imaging (RTI) is one of them, and it's utilized to enhance surface topography, including decorative features. Various imaging techniques are employed in conservation documentation to characterize the appearance and topography of a surface [1, 2]. RTI has mostly been used to investigate surfaces' technological and ornamental elements, such as improving the legibility of epigraphs or surface details [3, 4, 5]. However, there is a growing interest in using RTI data to document or monitor conservation treatments. Mainly case-study-based approaches have been offered this far [6, 7]. These case studies are based on typical data processing approaches that employ visualization tools to examine relightable images, perform specular enhancement, and analyze surface normals.

A few works are distinct for processing data beyond visualization tools, each taking a different method to change detection. To identify damaged areas on coins, Corregidor et al. (2020) applied edge detection techniques to RTI data [8]. To characterize the directionality of change on a mock-up painting before and after damage, Manfredi et al. (2013, 2014) suggested a methodology that looks at the documentation of topographic changes using surface normals [9, 10]. Following the surface normal deviation approach, Saha et al. (2022) proposed a semi-quantitative segmentation approach based on local normal distribution; however, the work clearly stated the need for image registration to quantify changes accurately [11]. To overcome the limitations of reconstruction models Dulecha et.al. (2020) [12] have proposed a neural network for more accurate surface visualization that, through edge detection, can detect surface cracks in an automated way [13].

Following an approach based on the analysis of raw RTI image data, Nurit (2022) proposed a series of algorithms for characterizing the visual appearance of manufactured surfaces, with application in industry [14] and advancing it to the semi-supervised segmentation based on surface saliency by le Goïc et al. (2022) [15]. The application of raw RTI data analysis based on features for the conservation documentation of CH metal surfaces was exploited by Siatou et al. (2022)[16]. Furthermore, Siatou et al. (2022) have explored the feasibility of monitoring corrosion based on these developments with application on silver tarnishing for assessing surface changes and determining the degree of corrosion [17]. The evaluation based on features reveals surface information related to condition assessment and semi-quantitative analysis of the resulting changes while providing spatial information in automated cartographies. However, automated change classification is not possible, and data interpretation requires expertise.

Condition mapping is an important part of conservation documentation, and this tedious work is usually performed manually or based on simple RGB image data [18]. Automation of this process through segmentation could help conservator-restorers to efficiently document the condition of an object and/or accurately monitor its condition over time. Furthermore, the application of RTI gives access to assess the textural and chromatic information of the surface's appearance attributes [19]. In this study, a novel method for describing the condition of cultural heritage (CH) metal surfaces is studied. It is based on advanced RTI data processing of the 16-dimensional Hemispherical Harmonics (HSH) coefficients [19].

The novel aspect of this work is the use of supervised segmentation on RTI data [20] to extract similar features that characterize different surface appearance attributes. To make the method more robust, invariant parameters of the RTI acquisitions (rotation, translation, illuminance, scale, etc.) were tested, and data normalization was adopted. The paper demonstrates the use of a segmentation method based on normalized HSH coefficients to detect changes in challenging CH surfaces such as metals. Furthermore, the geometric and optical properties of cultural heritage metal objects are exploited to study the reflectance response at different illumination angles.

Case Studies

The method was tested considering two case studies:

- Case study 1:Condition documentation on a surface with prominent topographic and color changes.
- Case study 2: Monitoring the evolution of corrosion on surfaces with minimal topographic changes and high color changes.

Case Study 1

This case study examines the condition documentation on a surface with prominent topographic and color changes. As an example, filiform corrosion on an iron surface was used. Filiform corrosion is related to organic coating failure through the creation of characteristic worm-like filaments that develop in the interface between a metal (usually aluminum or iron alloys) substrate, and a coated surface [21, 22]. These filaments provoke changes in the optical properties that reflect in the surface appearance attributes of the material by creating localized alterations due to the formation of corrosion products. These alterations manifest as color change (from metallic gray to brown-red iron oxides and oxi-hydroxides), and changes in local topography since the filaments are created on top of the metal substrate and have a more porous and less reflectance surface than the metal. For this case study, a filament created on an iron alloy lock coated with a transparent film or oil has been examined. The filament and the ROI selected for the experimental part are presented in Figure 1.

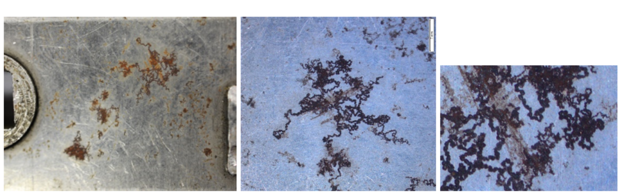

Figure 1. Selected area of the iron lock presenting filiform corrosion. Left: the area with characteristic filament, middle: microscopic observation of the filament, right: the ROI selected for the experimental part

Case Study 2

This case study examines the possibility of monitoring the evolution of corrosion on surfaces with minimal topographic and high color changes. As an example, silver tarnishing was examined. Silver corrodes in ambient indoor atmospheric environments mainly due to the presence of sulfur species. This type of corrosion is known to form a corrosion layer on the entire metal surface detected due to the change in color ranging from yellowish, for thin layers, to dark blue-black, for thicker ones [23, 24]. For the experimental part, flat test specimens (coupons) were prepared from pure silver (Ag 99.9%) and were then artificially tarnished using the protocol described in [17]. Three different textures were evaluated matt (diffusive), satin (anisotropic), and mirror (specular) (fig. 2), to examine the effect of texture in monitoring highly reflective surfaces. Five degrees of tarnish, ranging from reference 0 (no tarnish) to level 5 (high degree of tarnish), were created for each texture. The color difference between them varies from easy to hardly visible color changes between the various tarnish degrees. The results of the artificial tarnishing are presented in Figure 3. Due to the edge effect (more accelerated corrosion at the edges of the coupons), an ROI in the center of the coupon was selected for the experimental part.

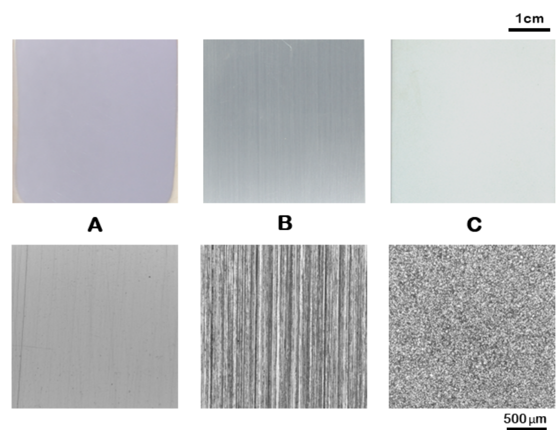

Figure 2. The textures of the silver coupons at different magnifications. From left to right: A mirror (highly specular surface), B satin (anisotropic with preferential directionality), and C matt (diffusive surface).

Methodology

The proposed supervised segmentation method incorporates the following major steps: data acquisition, normalization, supervision, discriminant model creation and prediction, and visualization.

Data Acquisition

RTI data were acquired using the custom-designed dome-based RTI system of the ImViA laboratory (University of Burgundy, Dijon, France). The system is equipped with a machine vision monochromatic camera (sensor Sony IMX304, resolution 4112(H) × 3008(V), 12.4MP) and a single light source (D65 illuminant). The system is motorized, allowing the selection of adjustable illumination angles and number of positions. High Dynamic Range RTI (HD-RTI) was selected to compensate for under- or over-saturated pixels due to the various illumination an-

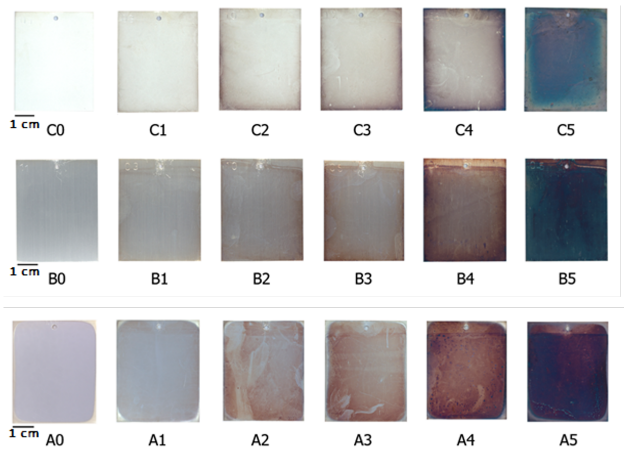

Figure 3. *The artificially tarnished silver coupons. Series A, B, and C correspond to the mirror, satin, and matt texture. From left to right, the degree of tarnish increases starting from the reference surface (0) and extending to heavy tarnish (level 5).*

gles [25]. 150 to 170 images were acquired for each data set in each case study to obtain an adequate amount of information accounting for computational time and data quality [26]. To ensure reproducibility, the same conditions (same position of the object, light source, number of light positions, illumination angles) were kept for cross-time data acquisitions.

Normalization

It is crucial to normalize the acquisitions taken at a certain time interval as this might incorporates several differences (such as object positioning, light count/source, scale, etc.) in collecting the data. By normalizing the HSH coefficients, we can overcome the differences in the acquisitions and bring them into one scale. Also, this will help in using the one-time training data to evaluate the surfaces over time. The calculated HSH coefficients for all image pixels are considered dataset **D** and rescaled by stretching or squeezing (Eq. 1) with the interval of [i, j where j > i]. In the proposed method, we default this interval at [-1,1].

$$\hat{\mathbf{D}} = i + [\mathbf{D} - D_{\min}]\frac{(j-i)}{D_{\max} - D_{\min}} \tag{1}$$

where, $\hat{\mathbf{D}}$ is normalized dataset of **D**, $D_{\min} = \min|(\mathbf{D})|$ and $D_{\max} = \max|(\mathbf{D})|$

Supervision

The supervision of the coefficients of each pixel was performed by considering a single instance of the RTI acquisition and annotating it based on expertise using the ”LabelMe Image Annotation Tool” [27] for each considered case study (Figure 4, Table 1). The groups for the segmentation are defined based on the research question during the supervision of the pixels. However, it has to be emphasized that while supervising the classes for selective pixels, one must have good knowledge of the surface appearance. For the case studies examined, this corresponded to a distinction between the localized areas exhibiting signs of filiform corrosion and the bulk of the metal substrate, creating thus two classes representing the corrosion and metal, respectively. In the case of silver tarnishing, the corrosion phenomenon affects the entire surface; therefore, areas in the center of the coupons are sufficient to represent the surface change. In this case, the classification was based on defining each level of tarnish for the different textures examined.

We then created a single discriminant model for each case study and applied the same to the surfaces to be assessed over time.

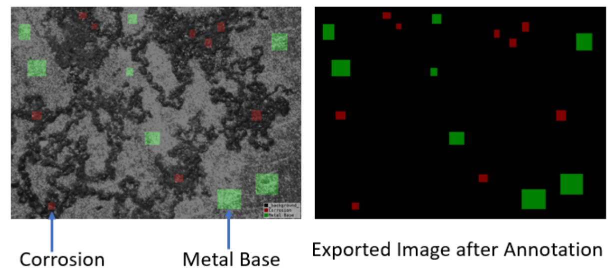

Figure 4. *Supervision on the LOCK (ROI)*

Training level assigned in the case of silver tarnish

Names	Level Assigned
C0,B0,A0	Level 0 (no corrosion)
C1,B1,A1	Level 1
C2,B2,A2	Level 2
C3,B3,A3	Level 3
C4,B4,A4	Level 4
C5,B5,A5	Level 5

Creating Discriminant Model and Prediction

The supervised normalized HSH coefficients are used to build discriminant models that predict changes in the surface's appearance over time based on each supervised class (C) using the RTI image stacks. Fisher's [28] multiclass separation model (Eq. 2) is used to generate the discriminant model for each case study.

Let us assume that each of the C classes has a mean μ_i and the same covariance σ. Then the scatter between class variability as σ_b can be defined by the sample covariance of the class means

$$\sigma_b = \frac{1}{C}\sum_{i-1}^{C}(\mu_i - \mu)(\mu_i - \mu)^T \tag{2}$$

where μ is the mean of the class means.

After creating the model for the selective pixels, it was evaluated for the entire surface and considered a trained model if the surface evaluation was accurate. Then, the trained data is used to evaluate the surfaces over time. The calculated and normalized HSH coefficients (sample data) for acquisitions taken over time are introduced to this model to predict the classes for each pixel based on the trained data.

Visualization

A simplified colormap representation is generated for each identified appearance category on the surface to make the results easily understandable by common users.

Results and Discussion

Case Study 1

The results of the supervised segmentation of filiform corrosion based on the two classes (corrosion and metal) are presented in Figure 5. In the visualization, the pixels corresponding to the filament are marked in blue and in yellow those of the metal substrate. Based on the comparison with visual observation of the surface (fig. 1), the method is able to segment the two surface characteristics incorporating the pixel similarities based on their reconstruction coefficient. This creates a clear division between the corrosion and the metal substrate due to the high difference in topography and color. HERE: I propose to add the quantification of pixels with the comment that the method doesn't only provide cartographies but allows pixel quantification. Through the calculation of the pixels marked with blue color, the percentage of the surface covered with filiform corrosion can be estimated. This segmentation can be useful in tracking changes over time (i.e., surface monitoring) by providing spatial and quantitative surface information.

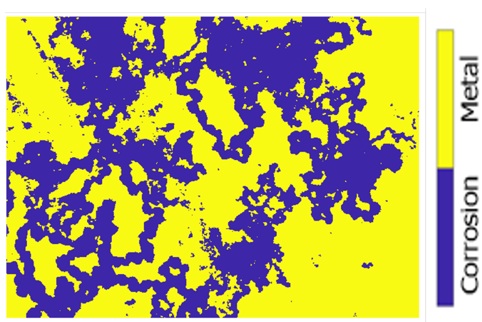

Figure 5. *Filiform corrosion results(ROI of the lock). The method allows the segmentation of the two classes: The blue class corresponds to pixel locations of filiform corrosion, and the yellow class to the metal.*

Case Study 2

In this case, data training was divided into six classes (levels 0 to 5) corresponding to the equivalent tarnish degrees (0 reference- no tarnish, 5 heavily tarnished). The ROIs selected for segmentation are in the center of the coupons at areas that present relatively homogeneous tarnish without significant patterns. The training was performed for each texture separately, and the coupons were then evaluated per texture based on the trained data. Representative results of the visualizations are presented in Figures 7, 6, and 8. On the left column, the training data are presented, and on the right, the results of the test data. The scale bar depicts the colors assigned to each level of tarnish per texture.

The results show the effect of texture on the acquisition of information based on the reflective properties of metal surfaces. Even at the level of data training, the method is limited to the correct segmentation of the matt surfaces. Data training of the mirror and satin surface shows the challenges of segmenting high specular and anisotropic surfaces. Figures 6, and 7 illustrate these challenges. The preferential directionality and the high specularity cause inhomogeneities in data registration that affect the estimation of the HSH coefficients and result in visualization that corresponds to heterogeneous surfaces. The trained data were tested on coupons to validate the applicability of the method. In the case of the matt (fig. 8) surfaces, the test results are properly classified. Demonstrating the ability of the proposed methodology to classify data based only on color differences. In the case of the mirror and satin surfaces, the test data reflect the train data and classify the test surfaces into segments that do not correspond to the actual tarnish levels. For example, in Figure 7 (top), the coupon with tarnish level 0 was selected; however, the train data assigned it to a mixture of levels 0 and 5. Respectively, the test data classify the same surface in level 2. Equivalently, in Figure 6 (top), the coupon with tarnish level 4 was selected; however, the train data assigned it to a mixture of level 2 with some pixels on levels 1 and 4-5. Respectively, the test data classify the same surface as mainly level 2. The resulting classifications are created due to the inability of the RTI to adequately capture anisotropic and mirror surfaces. Additionally, the surface change does not create topographic changes, and therefore surface similarities are based only on color variation expressed through the reconstruction coefficients.

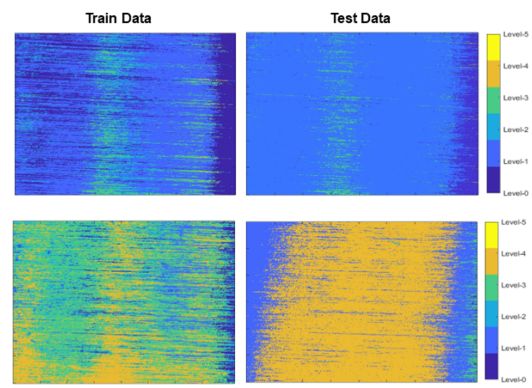

Figure 6. *Silver tarnish results on the satin surface finish. Left: Train data for levels 4 (top) and 5 (bottom). Right: Test data for levels 1 (top) and 4 (bottom).*

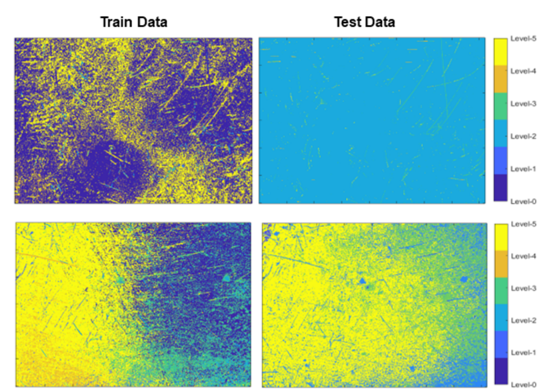

Figure 7. *Silver tarnish results on the satin surface finish. Left: Train data for levels 0 (top) and 5 (bottom). Right: Test data for levels 0 (top) and 5 (bottom).*

Conclusion-Discussion

The study's objective was to adapt the automated process of assessing surface appearance to track and visualize changes through advanced and interactive data processing collected from

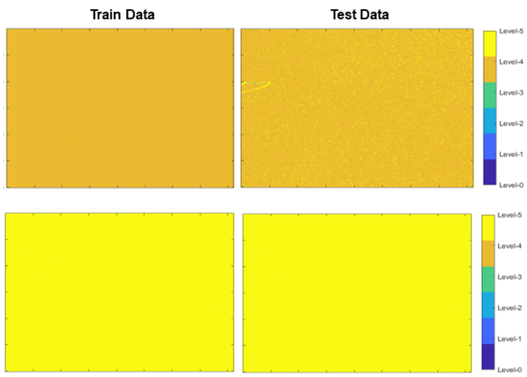

Figure 8. *Silver tarnish results on the matt surface finish. Left: Train data for levels 4 (top) and 5 (bottom). Right: Test data for levels 4 (top) and 5 (bottom).*

the RTI technique. The goal was to segment the surface's appearance characteristics, with visible changes, for conservation documentation in single instances or over time. A supervised segmentation method was applied to classify the reconstruction coefficients using linear discriminant analysis (LDA). The use of various acquisition parameters at different times or human mistakes when gathering data from the same surface were both addressed by the adaptation to the normalization of the derived reconstruction coefficients. The normalizing of the coefficients made it possible to compare two acquisitions taken from a surface at various time intervals by re-scaling them into a single scale, producing better results.

The proposed supervised segmentation of the RTI appearance attributes method was tested on two types of surface changes. One corresponding to changes with significant topographic and color differences and one with minimal topographic but high color difference. Also, the effect of the surface texture was examined in cases with changes with minimal topography but high color differences. In the first case, the changes between the different surface appearance attributes are prominent enough for the method to discriminate them and classify them with high accuracy. The segmented information can then be quantified and provide a clearer description of the surface condition. Detecting and classifying changes based on color differences using discriminant models deriving from the HSH coefficients was more challenging. The surface texture highly influences the resulting segmentation, and it was shown that it could only be accurately applied on diffusive surfaces. In conclusion, the resulting visualizations provide essential information on the surface's behavior and help automate change detection. Finally, although this work is evaluated and tested on metal cultural heritage surfaces, the technique could apply to different materials and various fields of expertise. Furthermore, the study can be extended, incorporating the RGB information (Multispectral RTI) into the feature space and improving the color segmentation for the presented second case study in the paper.

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Sunita Saha received her master's degree in computer science and engineering from NERIST (2018). She is currently doing her doctoral studies at the Faculty of Mechatronics at Warsaw University of Technology. Also, a Marie Curie ITN fellow (ESR4) at the EU project CHANGE. Her works focus on the analysis and visualization of multi-modal image data in CH surface monitoring over time or before and after the restoration process.

Amalia Siatou is a professional conservator-restorer (2004) with a master's in chemistry and material science (2013). Her studies and professional career have been devoted to conservation-restoration practices, scientific analysis, and evaluation of different cultural heritage materials. Between 2019-2022, she was a research assistant at HE-Arc CR and a Ph.D. candidate at the ImViA Laboratory at the University of Burgundy under the auspices of the CHANGE-ITN project.

Christian Degringy has a Ph.D. in analytical chemistry from the University of Paris IV on stabilizing submerged aluminum remains. He has since specialized in applying electrochemistry in conservation science and using imaging techniques by conservation professionals. He is currently a professor at HE-Arc CR.

Alamin Mansouri has been a computer science and imaging professor at the University Burgundy-Franche-Comté since 2006. He received his Ph.D. in computer vision in 2005 from the University of Burgundy. He has authored and co-authored more than a hundred scientific papers. His current research is focused on the computational modeling of visual perception through imaging.

Robert Sitnik (Member of OSA and SPIE) received his MSc Eng (1999), and Ph.D. (2002) in applied optics from the Warsaw University of Technology. He has authored and co-authored more than a hundred scientific papers. His interests are structured light shape measurement (3D/4D), triangulation methods, digital image processing, computer graphics, animation software development, and virtual reality techniques. He has been a leader in projects from various fields like 3D optical metrology, virtual and augmented reality, and supporting cultural heritage by Opto-numerical solutions. He is head of the Virtual Reality Techniques Division at WUT.