Computational Imaging for Cultural Heritage

Xiang Huang[a], Erich Uffelman[b], Oliver Cossairt*[a], Marc Walton[c], and Aggelos K. Katsaggelos[a]

a. Dept. of Electrical Engr. and Computer Science, Northwestern University, Evanston, IL, USA

b. Dept. of Chemistry and Biochemistry, Washington and Lee University, Lexington, VA, USA

c. Center for Scientific Studies in the Arts, Northwestern University, Evanston, IL, USA

*author to whom correspondence should be addressed: ollie@eecs.northwestern.edu

1. Introduction

Because art is inherently visual, use of imaging has long been an important way to understand its structure, form, and history. Recently, new ways of engaging with objects from our shared cultural heritage are possible with advances in computation and imaging that allow scientists to analyze art non-invasively, historians to pose new social questions about the art, and the public to explore and interact with art in ways never before possible. There is a rich history in applying image-processing techniques to conventional photographic images of works of art, many of which have been highlighted in previous special issues of this magazine (e.g., July issues 2008 and 2015). Building on these contributions, this paper comprises a survey of techniques where computation is central to the image acquisition process. Known as computational imaging, the methods being pioneered in this field are increasingly relevant to cultural heritage applications because they leverage advances in image processing, acquisition, and display technologies that make scientific data readily comprehensible to a broad cohort of non-technical researchers interested in understanding the visual content of art. Presently, only a small research community undertakes computational imaging of cultural heritage. Here we aim to introduce this burgeoning new field to a larger research community by discussing: 1) the historic background of imaging of art, 2) the burgeoning present day community of researchers interested in computational imaging in the arts, and finally, 3) our vision for the future of this new field.

The use of electromagnetic radiation, beyond the limits of eyesight, to visualize artworks may be traced to 1895 when Roentgen made his first X-ray shadowgraphs, one of which happened to have been a painted surface. However, it was not until the 1930's, when X-radiography first entered into museums, that a new art history formed around the ability to assess style and attribution of an artwork from aspects of the painted surface not visible to the naked eye [1]. This trend continued with other wavelengths of illumination. Specifically, UV-induced visible fluorescence helped reveal areas of loss/repair and provided a general sense of chemical composition [2]. By the late 1960's, infrared reflectography was in routine use in museums to reveal hidden underdrawings and preparatory marking in paintings [3]. More specialized techniques, such as autoradiography achieved by neutron bombardment of a work of art, opened up the possibility of combining elemental composition together with imaging for the first time [4] — a technique that would inspire further developments in X-ray fluorescence imaging several decades later [5]. By the 1980's, new 3D acquisition techniques were being explored for the 3D documentation and display of cultural objects, both of which remain relevant subjects of investigation to this day [6].

The recent explosion in imaging of cultural heritage has grown mainly out of the fields of remote sensing and color science. Of particular note is the use of hyperspectral and multispectral imaging instruments for pixel-by-pixel material characterization [7]. A parallel development has been the use of synchrotron-based X-ray fluorescence and diffraction imaging that has grown in conjunction with the diversification of users of these large-scale facilities from all research disciplines. Around the same time, computational illumination techniques were developed to dynamically re-light works of art in post-capture [8,9]. With the advent of inexpensive digital scanners, several researchers have focused on digitization of existing X-radiographs of canvas paintings, enabling recent advances in image processing algorithms to be applied to these historical works, such as in the canvas weave project initiated at Cornell University [10,11]. The proliferation of inexpensive digital sensors have been allowing museums to capture large amounts of high-resolution photographs in multiple modalities that were then computationally stitched together to provide seamless image mosaics with unprecedented detail [12]. Optical Coherence Tomography [13] and THz imaging [14] provide *in-situ* 3D reconstructions of microscopically thin layers of paint comprising pictures and drawings. At the other extremes of scale, the popularity of both LIDAR [15] and structure-from-motion techniques [16] have allowed us to search for ancient cities and document the historic landscapes of modern ones.

In the following sections of this paper, recent developments are discussed in four core areas that have served to advance the field of cultural heritage into new territory: Multispectral and Hyperspectral Imaging, 3D Shape Scanning and Recovery, Image Relighting, and Macro X-ray Imaging. Key developments in each of these areas have dramatically changed the landscape of how one non-invasively documents, assesses, interprets and conserves culturally significant artifacts housed in museums around the world.

2. Multispectral and Hyperspectral Imaging

Human eyes only perceives visible light (380nm ~ 750nm) with three types of color-sensitive cones: "red", "green", and "blue". Multispectral and hyperspectral techniques extend the measurable spectrum from visible light to ultraviolet (UV, 10nm ~ 380nm) and infrared (IR, 750nm ~ 1mm) lights with increased resolution: typically multispectral imagery has 3 ~ 10 bands, while hyperspectral imagery could have hundreds or even thousands of narrower (around 10nm) bands. Multispectral and hyperspectral imaging provide a wealth of information across space and wavelengths comprising large swaths of the electromagnetic spectrum. The techniques are also flexible since they can be scaled from the imaging of landscapes, when used on satellites and telescopes, down to the microscopic. Also, importantly, these imaging spectroscopies are non-destructive under the normal conditions of their implementation. Liang's recent review [17] should be consulted for developments in the field through 2012, but a brief introduction is provided here.

There are typically three principal ways of obtaining multi/hyperspectral data sets: (1) imaging the entire object at once through a series of different filters (or through a single filter whose bandpass characteristics may be controlled), (2) scanning a linear slit view of the object through a grating that spreads the relevant spectral region onto a 2D sensing array, (3) scanning the entire object point by point across its x-y surface [18]. Aspects of cost, time, and instrumental design parameters will dictate the choice of image acquisition method.

The resulting x-y surface images are “stacked” as a function of wavelength thus creating an image cube that may be interrogated in two ways. If the cube is “sliced” parallel to the x-y image face, one can analyze each of the images taken at each wavelength. Such an analysis at infrared wavelengths might readily provide an image of an under-drawing beneath the surface of a painting. If the stack is rotated by 90^o degrees to x-y image face of the cube, one can obtain multispectral responses from a wide range of spectrum at every pixel. Because chemical components have distinguishable spectral responses, multivariate statistical methods such as principal component analysis (PCA) can provide the identification of the material, such as pigment or binder, or both, present at that spot of a painting. Examining the PCA images, spectral angle maps of endmembers, or mapping regions of interest (ROIs) provide a wealth of information on the composition, execution, and condition of the art object even when an artist never employed a pure pigment in their composition and the consequential endmember spectra do not correspond to pure pigments.

Traditionally, these methodologies centered on the near UV, the visible, and the near IR. Recently, however, X-ray fluorescence spectroscopy (XRF), X-Ray diffraction analysis (XRD) macro scanning have moved these applications into a revolutionary new area of analysis (see Section 5 for more details). In addition, recent work involving mid-IR imaging [19] promises a wealth of new opportunities in cultural heritage analysis; *i.e.*, using the fingerprint region of the IR spectrum (a region typically thought of as ranging from roughly 400-1500 cm^{-1}, a range not completely available yet in commercial mid-IR scanners) enables mapping of a variety of pigments and binders, and comparison of the hyperspectral mid-IR data to point spectra obtained by a conventional IR spectrometer in reflectance mode demonstrates the power of this new technique, which should expand as the accessible mid-IR range of the instrumentation increases.

Currently, powerful combinations of multispectral and hyperspectral imaging with other imaging and analytical modalities are revealing the rich information that can be gleaned from the synergy of combined methodologies (e.g., Raman spectroscopy, fiber optic reflectance spectroscopy, compressive sensing) [7,20]. While multi/hyperspectral datacubes contain rich material information, they are challenging to acquire and analyze due to the sheer size of these datasets. Traditionally, dimension reduction and feature exaction techniques such as PCA and "end-member" analysis were used for hyperspectral data [18]. Recently, compressive sensing has been used in hyperspectral imaging for sensing, reconstruction and material classification [21]. The technique exploits the sparsity of signals by solving the following optimization problem:

$$\min_{f} \|f\|_p \text{, st. } \|g - Af\|_2 \leq \epsilon \text{,} \tag{1}$$

where ϵ controls the tolerate approximation due to noise, and p=0 or 1 describe the sparsity of the signal as L0 norm (total number non-zeros) or L1 norm (sum of absolute value).

The optimization framework from Equation (1) can be used to decompose measured reflectance spectra into pure spectral components, with can be used to identify and "unmix" heterogeneous pigment combinations on painting surfaces [22]. In this approach, *g* is defined as the spectral vector *g(λ)* at a given pixel, and each column of *A* is a spectral vector of known material from a pre-determined dictionary of pigment spectra. Solving the optimization problem then reconstructs the sparse coefficient f, which tells us the material components of that pixel, along with their relative concentrations. Note that these spectral decomposition methods are entirely linear, and therefore cannot accurately model non-linear effects such as wavelength-dependent scattering, self-absorption, etc., which may be common in a real painting material.

This section is concluded by highlighting a recent computational advance that leverages tremendous power from combined imaging modalities---i.e., advances in registration software that enable the "stacking" of images or especially the stacking of full data cubes from different regions of the electromagnetic spectrum [12].

The entire reason for manipulating data cubes from different regions of the electromagnetic spectrum— visualization of different and often complementary data— brings with it a concomitant challenge: is it possible to register images in which the features below the immediate surface have been moved, painted over, or scraped away? Artists often experimented with multiple under-drawings on the same painting and then over-painted those under-drawings with further alterations in the paint layers. Revealing and spatially registering these pentimenti can provide significant insights to artistic process and intent.

One solution [12] has utilized image fusion methods in which the modulus of the wavelet transform is determined and allows for the identification of "candidate control points", common features in the different images that can be used for alignment. The true functionality of the algorithm comes from how it assesses the statistical quality of these control points and seeks a wide enough spatial distribution of them so that a function may be calculated to register a variety of different sized images. Registration often requires a couple hours of computational time on a desktop PC. In the case of Figure 1, a rotated IR images has been registered with an X-radiograph followed by an adjustment of their relative intensities to clarify the legibility of the underlying portrait. This legibility enhances the confidence in assigning the underlying portrait to an artist other than Vermeer. [The reader is encouraged to view the movies of registered images in the supplementary materials of Conover, *et al.* [12] at http://link.springer.com/article/10.1007/s00339-015-9140-1] This software is not only exceptionally powerful, but it is also readily implemented; one of the authors of this paper routinely trains eighteen year old first year college students how to obtain multiple multispectral image cubes and to register them.

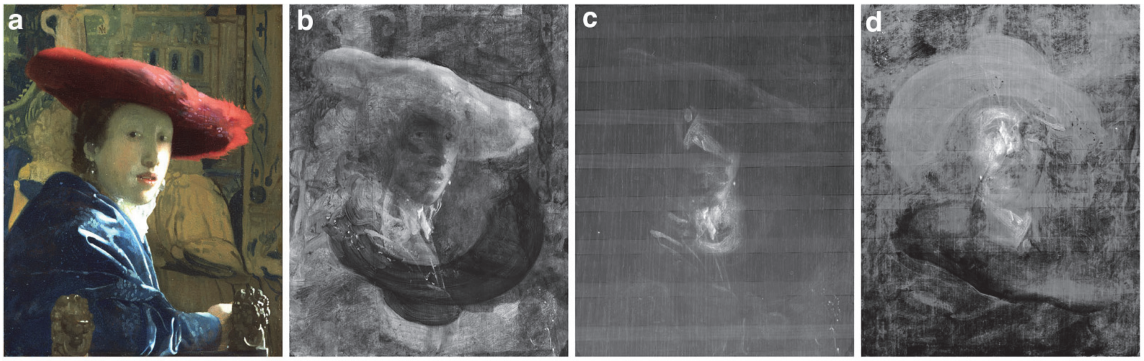

Figure 1 (images and figure caption from Conover *et al*. [12]). **A** Color image of Johannes Vermeer's Girl with the Red Hat (1665/1666). Andrew W. Mellon Collection, 1937.1.53, National Gallery of Art (NGA), Washington, D.C., **b** infrared reflectance (2100-2400 nm), c X-radiograph, and **d** summation of the rotated X-radiograph and the intensity-inverted and rotated infrared reflectance image.

3. 3*D* Shape Scanning and Recovery

Since the 1990*s*, 3*D* laser scanning has made the shape capture of 3*D* cultural-heritage objects possible. In one of the first efforts to capture sculpture in the round, the Digital Michelangelo project, researchers scanned several Michelangelo statues, including his masterpiece *David* [6]. While the project produced spectacular geometries of statues meters in size at *mm* resolutions from a combination of three expensive laser scanners, the results still fails with in specular/shinny areas of objects. Processing these data is also a non-trivial task since gaps in the scanned area must be filled and the different scans must be aligned and registered in X,Y,Z space. Also further processing to map color information on the acquired 3D meshes is needed to produce a fully rendered result. The whole process was expensive (2 million USD) and took 32 people years (1997-2004) to plan, scan and model of ten statues. Thus laser scanning poses many challenges that limit its widespread use. There is a clear need for developing new strategies for quick and cost effective ways for digitally archiving art.

Another effective approach to the imaging of extremely large structures has been airborne LiDAR (light detection and ranging) remote sensing techniques make it possible to record shapes on the extreme landscape scale. For instance, the 200 km^2 area of the ancient Maya landscape at

Caracol, Belize was scanned with a resolution that could resolve structures of roughly 25 cm height [15]. The data obtained helped researchers understand that the ancient Maya could radically modify their landscape to create a sustainable urban environment. The main limitation of this technique is the cost accessibility of the airborne craft, but new drones are quickly narrowing this gap.

To overcome some of the limitations of terrestrial and airborne laser scanning, researchers have more recently used a more convenient and purely image-based method, photogrammetry stereo technique known as "structure-from-motion" (SfM), to recover the shape of historical sites. In 2006, the 3*D* structure of the Colosseum in Rome was generated from a large collection of consumer photos taken at different viewpoints [16]. These photos were gathered from an internet sharing website. The photo explorer uses image-based rendering techniques to create smooth transition between different viewpoints, so the user can comfortably tour historic locations virtually. SfM may also be used to great effect on smaller moveable objects, however the depth accuracy of the photogrammetry stereo method is limited to only textured surfaces and fails on featureless surfaces, hence the depth resolution is typically lower than the lateral resolution at each pixel.

Another image-based method, photometric stereo, , recovers the 3D shape of an object by taking multiple images at fixed view but varies lighting positions. Photometric stereo models the image intensity as a function of surface normal, reflectance, and lighting/viewing angle. The surface normal is recovered by solving an optimization problem, and the 3D surface of the object can be recovered by integrating the surface normal across the field of view. Unlike photogrammetry, photometric stereo works extremely well on texture-less surfaces and can produce high resolution normal maps. Classic photometric stereo methods assume a point light source placed at infinitely far away from direction L, and assume the material is Lambertian with albedo reflectivity of k, so that the reflected light intensities becomes

$$I = k(n \bullet L)\,. \tag{2}$$

By taking a series of measurements *I*, with different, but known lighting direction *L*, the surface normal *n* and albedo *k* can be estimated from a system of linear equations using, for instance, a least squares method.

Classical photometric stereo assumes a distant-light model. This considerably simplifies the problem, as it produces constant lighting angle and incident radiance across the object surface. However, distant light sources are impractical due to finite space and energy constraints. As a result, for a typical photometric stereo capture setup, lighting angle and incident radiance vary across the object surface. Using the simplified far-light model from Equation (2) with such a setup produces a 3D shape with large global error [9]. Recently, researchers have explored near light photometric stereo method to recover millimeter to sub mm-scale markings on the surfaces Paul Gauguin's paintings (Figure 2) [9]. The depth maps acquired achieve a depth precision of less than 100 microns for a field of view as large as 300 mm. These depth maps have revealed new details of how Gauguin produced his paintings using his unique drawing transfer techniques.

Figure 2 (images and figure caption from Cossairt *et al*. [9]). **Left.** The setup for capturing photometric stereo of Gauguin's *Nativity*: a color checker for color calibration, a 3D calibration target for 3D surface calibration, a reflective sphere for calibrating light direction, and the work of art. **Right.** Several frames from an animation visualizing the 3D surface shape at the location of the lines drawn in *Nativity*. The 3D reconstruction shows clear evidence of protrusions on the page where ink has been deposited. This is solid evidence for the ink being transferred from a matrix such as that in a monotype transfer process.

Classical photometric stereo assumes Lambertian surfaces with perfect diffuse reflection. However, this assumption is invalid for a large class of real materials such as metals, plastics and glass, which exhibit different combinations of diffuse and specular reflections. The most accurate way to model how light is reflected from an opaque surface uses the bidirectional reflectance distribution function (BRDF). The BRDF is a 4D function $f_r(\omega_i, \omega_o)$ which depends on the incoming light direction ω_i and outgoing light direction ω_o. The BRDF is the most general way to model surface reflection, but it also severely complicates the photometric stereo problem. As a result, several researchers have investigated lower dimensional reflectance models for use with photometric stereo algorithms. Ikehata et al. [23] models the non-Lambertian, specularities and shadows as additive corruption E, so that the observed image intensity is $I = k(n \bullet L) + \mathrm{E}$. Assuming the corruption E is spatially sparse, the problem can be solved by compressive sensing algorithms by modeling the optimization similar to the Lagrange form of Equation (1) as:

$$\min_{k,n,E} \; \left\| I - k(n \bullet L) - \mathrm{E} \right\|_2 + \lambda \left\| E \right\|_0, \tag{3}$$

where λ is an nonnegative parameter controls the balance between data fit with sparsity.

While photometric stereo can produce sub-millimeter precision surface measurements, other methods can be used to measure surface detail on the microscopic scale. Optical Coherence Tomography (OCT) has recently been employed for examining the layer structure of paintings [13]. High-resolution 3*D* images at a micron scale can be reconstructed thus revealing the under-layers of paintings and their corresponding depth positions. Originally proposed for biomedical imaging of structures such as the eye, OCT can produce high-resolution contrast depth maps. OCT presents challenges in that the instrumentation is expensive and can only scan centimeter-sized areas. The depth maps obtained are also not linked to material color information, so interpreting these data is not immediately intuitive.

4. Image Relighting for Cultural Heritage

In addition to the $3D$ geometry, characterizing surface appearance under different lighting conditions is also critical for cultural heritage. Appearance of an artwork is the sum result of how its material and microstructure interact with all possible incoming light rays and all the possible subsequent measured outgoing light rays which may have been reflected, absorbed, scattered, refracted, and transmitted from the artwork's surface. This compressive light-transport function combines each possible incident light location, wavelength, direction, polarization with how this incident electromagnetic radiation scatters underneath the object's surface and global illumination effects such as self-shadowing and inter-reflection. It is an immense totality of measurements that is only theoretically possible to collect completely. Consequently, the light-transport function at a fixed view point may be easier to gather by capture images of artwork lit from various light directions. Reflectance Transformation Imaging (RTI), originated from Polynomial Texture Mapping (PTM), is one such approximation method. Malzbender [8] first discussed RTI as a method for examining an artwork using interactively changeable lighting conditions with a set of digital images. By interpolating multiple images of a work, each with different illumination angles from a fixed camera position, an 'active photo' may be produced with easy controls that encourage exploration to see vanishingly-subtle features, including self-shadowing and inter-reflection. The PTM typically stores six coefficients $c = [c_0, c_1, c_2, c_3, c_4, c_5]$ for each pixel, and compute the pixel intensity I from a novel illumination direction $l = [l_x, l_y, l_z]^T$ as a biquadratic function:

$$I = c_0 l_x^2 + c_1 l_y^2 + c_2 l_x l_y + c_3 l_x + c_4 l_y + c_5 . \tag{4}$$

The RTI either uses above polynomial basis $h(l) \triangleq [l_x^2, l_y^2, l_x l_y, l_x, l_y, 1]^T$ of order six or higher, or uses hemi-spherical harmonics (HSH) basis $h(l)$ to generate a novel image from a new illumination direction l interactively specified by a user. For both case, the pixel intensity is universally given by $I = h(l)^T c$. While the basis $h(l)$ is the same for all the image pixels, the coefficients c are pixel dependent. The coefficients can be computed from a set of pre-captured K

images under different known lighting directions, by least squares of an over-determined (assume c has less order than K) linear system:

$$\begin{bmatrix} h(l_1) \\ h(l_2) \\ \vdots \\ h(l_K) \end{bmatrix} c = \begin{bmatrix} I_1 \\ I_2 \\ \vdots \\ I_K \end{bmatrix} . \tag{5}$$

Over the past several years, the art conservation community has adopted RTI for close digital examination of artworks through relighting. RTI provides visually compelling ways to interactively explore surface relief and discover subtle surface features otherwise missing or indiscernible in ordinary photos or by direct visual inspection [24]. The free viewer software from Cultural Heritage Imaging (CHI) has been a boon to the field since it can exaggerate surfaces, pixel-by-pixel, to depict the topography more clearly and to compute estimates of surface normal vectors via photometric stereo or from the PTM interpolation equation itself.

However, these methods assume that lighting is infinitely far away from the object, a condition that cannot be easily achieved in practice due to power limitations of the light source and limited space around the object. The obvious solution is to capture images using near lighting, but these conditions result in non-uniform illumination artifacts made worse as the distance between the light source and scene narrows. Not only does uneven illumination produce poor visualizations for relighting, but when these data are used for photometric stereo, systematic errors introduce curl to the surface normal estimations and make quantitative surface reconstructions difficult. An algorithm to correct for captures that violate far-light assumptions has recently become available [25] that creates uniformly lit images (Figure 3) and, moreover, accurate photometric stereo calculations for estimation of surface normals.

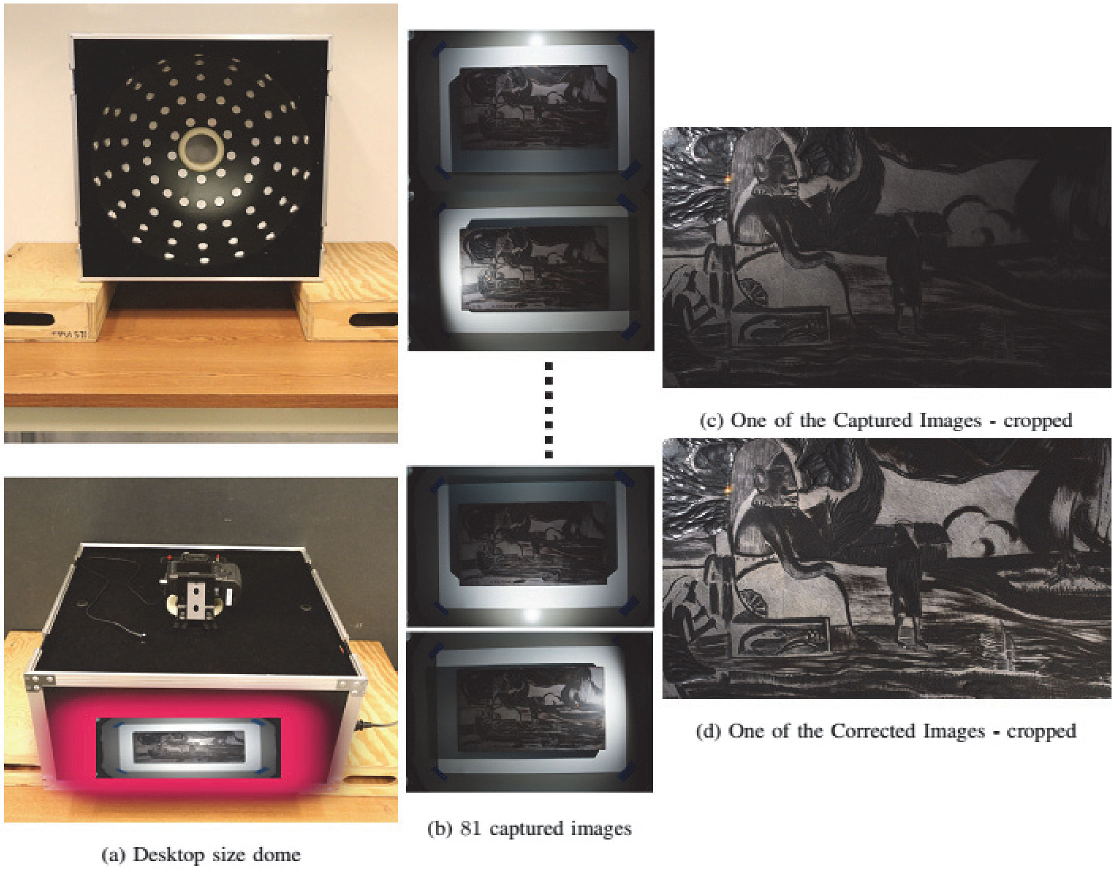

Figure 3 (images and figure caption from Huang, *et al.* [25]): Relighting comparisons for a woodblock by Paul Gauguin (accession number 1940-91) housed at the Art Institute of Chicago. The woodblock was inserted under a dome (a) to capture 81 images, each under different lighting (b). The light position used to compute light attenuation due to the distance squared fall-off. The inverse of this attenuation was used to produce relit images with even illumination (c). The corrected images look uniformly lit and more visually pleasing (d).

5. Macro X-ray Methods

All macro X-ray methods in cultural heritage stem from Roentgen's discovery of X-rays in the late 19th century. X-radiography has been a staple of the field for decades and still is valuable in its original form: a contrast image formed from the absorption of X-rays by high-Z contrast elements, such as the lead associated with the pigment lead white. X-radiographs are routinely used by conservators and curators to characterize the method and style of painting and can be indicative of the artist's thought process when *pentimenti* are observed. Within the last decade, major advances have been made in interpreting X-radiographs by computational methods. Also, there has been an increasing use of macro tomographic methods, as well as the development of macro XRF scanning and macro XRD scanning that have transformed our views of cultural heritage objects.

5.1 Computational Processing of X-radiographs

Computational processing of X-radiographs has revolutionized the area of thread count and thread direction analysis for paintings on fabric supports [11] and now the chain lines are impressed into the paper by the wire mesh of the moulds during fabrication [26]. The development of the method in [11] hinged on realizing that a Fourier transform to the observed alternating light and dark X-ray contrast patterns of a canvas could provide both thread count and thread direction data. Prior to this insight, threads were painstakingly counted by hand under magnification, and those counts were limited to only a few centimeters of a painting.

These new computational methods permit global analysis of the entire work. The overall pattern of threads has been shown to be very diagnostic for matching paintings to a single bolt of fabric and is now being used to date paintings. Furthermore, primary and secondary cusping in the canvas weave (scallop patterns caused by the stretching methods used to prepare canvases for old master paintings) becomes obvious after employing the computational algorithm, and not only can these patterns be used to match paintings to proximal regions of a bolt of cloth, their absence can be used to infer that a painting has been trimmed. More importantly, this method provides a way to match paintings at approximately the same period to a single bolt of cloth [11].

5.2 Macro XRF Scanning

Some of the most exciting recent developments in cultural heritage analysis have involved XRF. The method involves using an X-ray source to ionize core electrons from atoms or ions. After the generation of inner-shell electron "holes", higher energy electrons "fall" into those holes, leading to the fluorescence of an X-ray. Because electron energy levels are quantized, the fluoresced X-rays are characteristic of the elements involved. Because inner-shell electrons are involved in these processes, the technique gives only elemental rather than chemical information. Therefore, for better and for worse, the spectra are simplified by their lack of chemical information.

X-rays of different energies are attenuated different amounts when passing through a given material from emitter to detector. As a result, it is possible to make some statements regarding the depth of materials relative to one another in the layers of a painting, particularly when a model of that layered material can be computer simulated [27]. For example, the difference in intensity for an element's spectral response compared to theory can indicate how close to the surface of the object that element is, given information from the spectrum about which elements might be on top of it. Highly portable, rugged XRF point analyzers have made it possible to do qualitative (and under favorable conditions, semi-quantitative) elemental analysis non-destructively on cultural heritage objects in a matter of minutes.

The true revolution in the field has resulted from taking XRF scanning methodologies and repurposing them with transportable macro XRF scanners [5,28]. These scanners acquire a hyperspectral XRF data cube by scanning point by point in the x-y plane---each point in the x-y plane contains a full XRF spectrum. As with single point analysis, depth information can often be inferred based on relative X-ray intensities. As one might imagine, the amount of data involved in these cubes has demanded computational methods that can handle and mine this wealth of information [29]. Sometimes scanning a painting on a canvas support from behind can provide a better data set, due to different X-ray absorption characteristics, than scanning a painting from the front. The resulting information about elemental composition can be used to infer pigment maps and inferred information about relative depth can be used in combination with those maps to reconstruct paintings underneath overpaint [28]. For an artist such as van Gogh, whose work sold so poorly during his lifetime that he was supported by his brother and frequently reused his canvases, this XRF scanning technique has opened vast new areas of research (Figure 4).

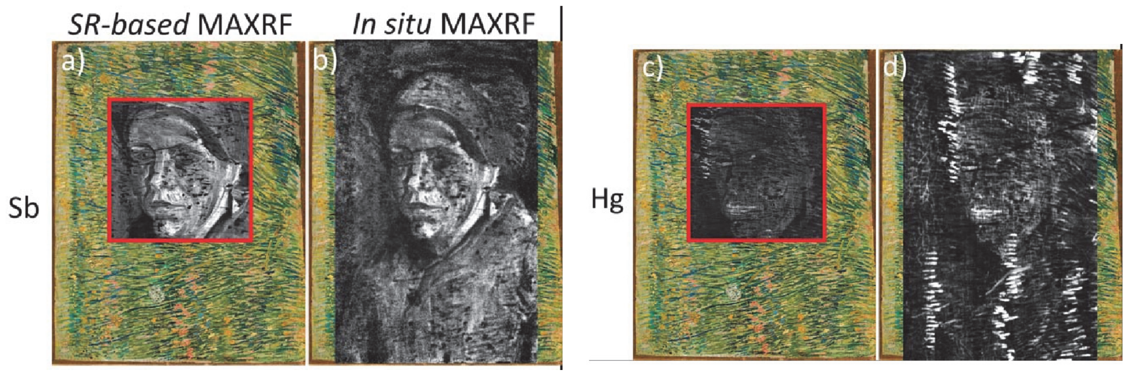

Figure 4 (images and figure caption from Alfeld, *et al.* [28]). Elemental maps, obtained on Vincent van Gogh's ''Patch of Grass'', showing the hidden portrait of a woman. (a) and (b) show the Sb distribution, while (c) and (d) show the Hg distribution. (a) and (c) were acquired with macro-XRF at a synchrotron source, while (b) and (d) are results of in situ measurements by means of Instrument B. (a) and (c) were acquired with a step size of 0.5 mm and 2 s dwell time in two days, while (b) and (d) were acquired with a step size of 1 mm and a dwell time of 5.1 s in six days.

5.3 Macro XRD Scanning

As with point XRF analysis, point powder XRD has historically been invaluable in the characterization of artists' pigments. When performed *in situ*, the method does not require a sample and is considered nondestructive. Because the diffraction of X-rays requires a regular repeating array of electron density, the method requires microcrystallinity in the analyte. Thus, the technique cannot be used on amorphous materials or materials that do not diffract X-rays well, and in this regard it is inferior to XRF. However, because the diffraction pattern of a crystalline substance is essentially a fingerprint, it provides direct chemical information about the analyte, and in that regard it is superior to XRF. Because XRD typically requires greater photon flux than XRF, the method was more resistant to migration from synchrotrons to transportable scanning methodology. Fortunately, those problems are being solved [5]. In addition to providing positive chemical identification of materials present, XRD also offers the advantage that, because it requires higher energy X-rays, it provides greater depth penetration. Combined with XRF macro scanning data cubes and hyperspectral imaging cubes from the UV, vis, and IR, these techniques, operating synergistically, allow unprecedented insights into the composition of cultural heritage objects, with all of the attendant implications for art history and art conservation.

6 Concluding Remarks

In this summary, how computational imaging has impacted five key areas of cultural heritage science has been surveyed. There are three key features that have resulted in these techniques making a significant impact on the cultural heritage community. The first is the proliferation in recent years of image sensing technology, which has spawned technological advances in new imaging modalities such as XRF, XRD, hyperspectral, etc. The second feature is, recent advances in these new imaging modalities has given accessibility to entirely new types of information latent within the artworks held by museums. The third feature is the ability to visualize information about artifacts intuitively in the form of images, which has made this information much more accessible and comprehensible to non-experts.

Computational imaging of cultural heritage is opening up many new avenues for investigating the technical art history of objects and to assess the condition of works of art that will aid in their long-term preservation. There are several areas of computational imaging that have not been thoroughly explored on cultural heritage objects. Also compressive sensing and sparse imaging could significantly improve sensitivities especially for conditions where low light is necessary for light-sensitive materials and when increased imaging speeds are necessary for experiments that cannot be conducted in the public spaces of museums over days (as in macro x-ray scanning). Improved material databases with bi-directional reflectance distribution function data [30] could lead to advances in reconstruction algorithms that produce more accurate image archives and renderings. Scalability is another principal obstacle. For example, a comprehensive measurement of the chemical composition and spatial structure of layers of paint in an entire work of art could provide new and valuable tools for art historians and conservators.

Another important direction that has not been covered in this review is the dissemination, visualization, and display of the great body of visual information now being captured by museums and galleries around the world. For instance, augmented reality is projected to strongly impact the museum visitor experience in coming decades. Lastly for the computational imaging field it is important to note that artworks provide fantastic test scenes that can inspire researchers to push the envelope by providing new imaging and display techniques that can probe the complex light-material interactions inherent in so many works of art. In this regard, it is the hope that cultural heritage can serve as a catalyst for novel research in computational imaging.

Xiang Huang is currently a postdoctoral researcher in the Mathematics and Computer Science Division of Argonne National Laboratory. Xiang Huang is interested in solving challenging problems in Computational Photography, Image Processing, Machine Learning and Computer Vision.

Erich Uffelman is the Bentley Professor of Chemistry at Washington and Lee University. He obtained his PhD from the California Institute of Technology as an NSF Predoctoral Fellow in 1991, and performed work as an NIH Postdoctoral Fellow at Stanford until he joined the W&L faculty in 1993. He has had numerous grants and publications and was a winner of the 2009 State Council of Higher Education of Virginia Outstanding Faculty Award.

Oliver Cossairt is an Assistant Professor at Northwestern University, within the Electrical Engineering and Computer Science department. He directs the Computational Photography Laboratory, whose research consists of a diverse portfolio, ranging in topics from optics/photonics, computer graphics, computer vision, and image processing.

Marc Walton currently runs the Northwestern University / Art Institute of Chicago Center for Scientific Studies in the Arts (NU-ACCESS) as its Senior Scientist and he holds a joint appoint as a Research Associate Professor in the department of Materials Science and Engineering at Northwestern University. Dr. Walton's research has focused primarily on the trade and manufacture of ancient objects and he has published extensively in the fields of archaeological science and technical art history.

Aggelos K. Katsaggelos is currently a Professor holder of the Joseph Cummings chair in the Department of Electrical Engineering and Computer Science at Northwestern University. He has published extensively in the areas of multimedia signal processing and communications, computational imaging and machine learning (7 books, over 250 journal papers, 500 conference papers and 40 book chapters) and he is the holder of 25 international patents.

References

[1] Burroughs, A. *Art Criticism from a Laboratory*; Little, Brown and Company: Boston, 1938.

[2] Rorimer, J. J. *Ultra-violet Rays and their use in the Examination of Works of Art*; Metropolitan Museum of Art: New York, 1931.

[3] van Asperen de Boer, J. R. J. "Reflectography of Paintings using an Infrared Vidicon Television System" *Studies in Conservation*, vol. 14, pp. 96-118, 1969.

[4] Sayre, E. V.; Lechtman, H. N. "Neutron activation autoradiography of oil paintings" *Studies in Conservation*, vol. 13, pp. 161-185, 1968.

[5] Legrand, S.; Vanmeert, F.; Snickt, G. V. d.; Alfeld, M.; Nolf, W. D.; Dik, J.; Janssens, K. "Examination of historical paintings by state-of-the-art hyperspectral imaging methods: from scanning infra-red spectroscopy to computed X-ray laminography" *Heritage Science*, vol. 2, pp. 2-13, 2014.

[6] Levoy, M.; Pulli, K.; Curless, B.; Rusinkiewicz, S.; Koller, D.; Pereira, L.; Ginzton, M.; Anderson, S.; Davis, J.; Ginsberg, J.; Shade, J.; Fulk, D. "The digital Michelangelo project: 3D scanning of large statues" *Proceedings of the 27th annual conference on Computer graphics and interactive techniques - SIGGRAPH '00.*, ACM Press/Addison-Wesley Publishing Co., 2000.

[7] Delaney, J. K.; Ricciardi, P.; Glinsman, L. D.; Facini, M.; Thoury, M.; Palmer, M.; de la Rie, E. R. "Use of imaging spectroscopy, fiber optic reflectance spectroscopy, and X-ray fluorescence to map and identify pigments in illuminated manuscripts" *Stud. Conserv.*, vol. 59, pp. 91-101, 2014.

[8] Malzbender, T.; Gelb, D.; Wolters, H. "Polynomial texture maps" *Proceedings of the 28th Annual Conference on Computer Graphics and Interactive Techniques, SIGGRAPH 2001*, 2001.

[9] Cossairt, O.; Huang, X.; Matsuda, N.; Stratis, H.; Broadway, M.; Tumblin, J.; Bearman, G.; Doehne, E.; Katsaggelos, A.; Walton, M. "Surface Shape Studies of the Art of Paul Gauguin" *Digital Heritage Granada Conference*, 2015.

[10] C. Richard Johnson, J.; Hendriks, E.; Berezhnoy, I. J.; Eugene Brevdo; Hughes, S. M.; Daubechies, I.; Jia Li, E. P.; Wang, J. Z. "Image Processing for Artist Identification" *IEEE SIGNAL PROCESSING MAGAZINE*, vol. July, pp. 37-48, 2008.

[11] Johnson, D. H.; Johnson, C. R., Jr.; Erdmann, R. G. "Weave analysis of paintings on canvas from radiographs" *Signal Processing*, vol. 93, pp. 527-540, 2013.

[12] Conover, D. M.; Delaney, J. K.; Loew, M. H. "Automatic registration and mosaicking of technical images of Old Master paintings" *Appl. Phys. A: Mater. Sci. Process.*, vol. 119, pp. 1567-1575, 2015.

[13] Liang, H.; Cid, M. G.; Cucu, R. G.; Dobre, G. M.; Podoleanu, A. G.; Pedro, J.; Saunders, D. "En-face optical coherence tomography - A novel application of non-invasive imaging to art conservation" *Optics Express*, vol. 13, pp. 6133-6144, 2005.

[14] Jackson, J. B.; Mourou, M.; Whitaker, J. F.; Duling Iii, I. N.; Williamson, S. L.; Menu, M.; Mourou, G. A. "Terahertz imaging for non-destructive evaluation of mural paintings" *Optics Communications*, vol. 281, pp. 527-532, 2008.

[15] Chase, A. F.; Chase, D. Z.; Weishampel, J. F.; Drake, J. B.; Shrestha, R. L.; Slatton, K. C.; Awe, J. J.; Carter, W. E. "Airborne LiDAR, archaeology, and the ancient Maya landscape at Caracol, Belize" *Journal of Archaeological Science*, vol. 38, pp. 387-398, 2011.

[16] Snavely, N.; Seitz, S. M.; Szeliski, R. "Photo tourism: Exploring photo collections in 3D" *ACM SIGGRAPH 2006 Papers, SIGGRAPH '06*, 2006.

[17] Liang, H. "Advances in multispectral and hyperspectral imaging for archaeology and art conservation" *Appl. Phys. A: Mater. Sci. Process.*, vol. 106, pp. 309-323, 2012.

[18] Eismann, Michael Theodore. "Hyperspectral remote sensing." Bellingham: SPIE, 2012.

[19] Rosi, F.; Miliani, C.; Braun, R.; Harig, R.; Sali, D.; Brunetti, B. G.; Sgamellotti, A. "Noninvasive Analysis of Paintings by Mid-infrared Hyperspectral Imaging" *Angew. Chem., Int. Ed.*, vol. 52, pp. 5258-5261, 2013.

[20] Cesaratto, A.; Nevin, A.; Valentini, G.; Brambilla, L.; Castiglioni, C.; Toniolo, L.; Fratelli, M.; Comelli, D. "A novel classification method for multispectral imaging combined with portable Raman spectroscopy for the analysis of a painting by Vincent Van Gogh" *Appl. Spectrosc.*, vol. 67, pp. 1234-1241, 2013.

[21] R. M. Willett, M. F. Duarte, M. A. Davenport and R. G. Baraniuk, "Sparsity and Structure in Hyperspectral Imaging : Sensing, Reconstruction, and Target Detection," in IEEE Signal Processing Magazine, vol. 31, no. 1, pp. 116-126, Jan. 2014.

[22] M. Iordache, J. M Bioucas-Dias, and A. Plaza, “Sparse unmixing of hyperspectral data,” Geoscience and Remote Sensing, IEEE Transactions on, vol. 49, no. 6, pp. 2014–2039, 2011.

[23] S. Ikehata, D. Wipf, Y. Matsushita and K. Aizawa, "Robust photometric stereo using sparse regression," Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on, Providence, RI, 2012, pp. 318-325.

[24] Mudge, M.; Malzbender, T.; Schroer, C.; Lum, M. In *VAST 2006, The 7th International Symposium on Virtual Reality, Archaeology and Cultural Heritage*; Ioannides, M., Arnold, D., Niccolucci, F., Mania, K., Eds. Nicosia, Cyprus, 2006.

[25] Huang, X.; Walton, M.; Bearman, G.; Cossairt, O. "Near Light Correction for Image Relighting and 3D Shape Recovery" *Digital Heritage Granada Conference*, 2015.

[26] C. Richard Johnson, J.; Sethares, W. A.; Ellis, M. H.; Haqqi, S. "Hunting for Paper Moldmates Among Rembrandt’s Prints" *IEEE SIGNAL PROCESSING MAGAZINE*, vol. July, pp. 28-37, 2015.

[27] de Viguerie, L.; Walter, P.; Laval, E.; Mottin, B.; Sole, V. A. "Revealing the sfumato Technique of Leonardo da Vinci by X-Ray Fluorescence Spectroscopy" *Angew. Chem., Int. Ed.*, vol. 49, pp. 6125-6128, S6125/6121-S6125/6123, 2010.

[28] Alfeld, M.; Janssens, K.; Dik, J.; de Nolf, W.; van der Snickt, G. "Optimization of mobile scanning macro-XRF systems for the in situ investigation of historical paintings" *Journal of Analytical Atomic Spectrometry* vol. 26, pp. 899-909, 2011.

[29] Alfeld, M.; Janssens, K. "Strategies for processing mega-pixel X-ray fluorescence hyperspectral data: a case study on a version of Caravaggio's painting Supper at Emmaus" *J. Anal. At. Spectrom.*, vol. 30, pp. 777-789, 2015.

[30] Ashbaugh, J. C.; Berns, R. S.; Darling, B. A.; Taplin, L. A. "Artist material BRDF database for computer graphics rendering" *Final Program and Proceedings - IS and T/SID Color Imaging Conference*, 2009.