DIGITAL IMAGE PROCESSING IN PAINTING RESTORATION AND ARCHIVING

N. Nikolaidis and I. Pitas

Department of Informatics, Aristotle University of Thessaloniki
Thessaloniki 54006, Greece
E-mail: pitas@zeus.csd.auth.gr

ABSTRACT

Digital image processing and analysis can be an important tool for the restoration of works of art. This paper presents three applications of image processing in this field: a method for digital crack restoration of paintings, a technique for color restoration of old paintings and a method for mosaicing of partial images of works of art painted on curved surfaces. A digital archiving system for works of arts is also described.

1. INTRODUCTION

Painting restoration is a very demanding field that requires considerable expertise. Since most of the restoration procedures (e.g. chemical cleaning of dirt layers) are irreversible, a great amount of planning is necessary before each operation, especially when the work of art that is being restored is of great historical and artistic importance.

Digital image processing and analysis can be of great help to painting restoration experts, museum curators and art historians, its contribution being two-fold: (a) provision of a non-destructive way to plan and test a restoration operation in a virtual way (i.e. on a digital image), before proceeding to its actual implementation on the painting, (b) provision of clues to art historians and the general public on how the painting would look like in its initial state i.e., without the physical damage. Three applications of image processing in restoration of paintings are presented in this paper: a method for digital crack restoration of paintings, a technique for color restoration of old paintings and a method for mosaicing of partial images of works of art painted on curved surfaces.

Another technological achievement that had a great impact on the art circuit is the introduction of database management systems. Such a system, tailored to the needs of archiving and cataloguing of paintings is also presented in this paper.

2. DIGITAL COLOR RESTORATION OF PAINTINGS

Varnish oxidation is a phenomenon that can degrade the visual appearance of old paintings. Dirt, smoke, and other deteriorations can further degrade the appearance of paintings. The result is that colors faint and the painting appears brown or black. This is particularly true for icons or church murals, where candle smoke degrades icon colors. The removal of this oxidation layer is performed by conservation experts through a time-consuming process which does not always guarantee success. In many cases, a trial and error approach is implemented on small parts of the painting in order to select the most appropriate substance to be used to clean the entire painting. Digital image processing techniques can be used to simulate color restoration without extensive chemical cleaning of the painting surface.

Let us assume that certain uniformly colored regions of the painting that are representative of its color gamut have been cleaned chemically and that the respective patches have been digitized. These constitute the "clean" image data sets $\mathbf{s}_i,\ i = 1, \ldots, N$, each including a number of pixels. We also digitize the same regions before cleaning, or dirty regions having the same paint. These data form the "dirty" image data sets $\mathbf{x}_i,\ i = 1, \ldots, N$. The way of choosing the two sets ensures that there is a one to one correspondence of their elements, i.e., $\mathbf{s}_i$ is the "clean" version of $\mathbf{x}_i$.

Let the vectors $\hat{\mathbf{m}}_{\mathbf{s}_i}$ and $\hat{\mathbf{m}}_{\mathbf{x}_i}$, $i = 1, \ldots, N$, represent the sample mean of the ith clean and oxidized region, respectively. Furthermore, let $\hat{\mathbf{m}}_{\mathbf{s}}$ and $\hat{\mathbf{m}}_{\mathbf{x}}$ denote the sample mean matrices of the clean and oxidized regions, respectively:

$$\begin{aligned} \hat{\mathbf{m}}_{\mathbf{s}} &= [\hat{\mathbf{m}}_{\mathbf{s}_1} \quad \hat{\mathbf{m}}_{\mathbf{s}_2} \quad \cdots \quad \hat{\mathbf{m}}_{\mathbf{s}_N}] \\ \hat{\mathbf{m}}_{\mathbf{x}} &= [\hat{\mathbf{m}}_{\mathbf{x}_1} \quad \hat{\mathbf{m}}_{\mathbf{x}_2} \quad \cdots \quad \hat{\mathbf{m}}_{\mathbf{x}_N}] \end{aligned} \tag{1}$$

and $\Delta\hat{\mathbf{m}} = \hat{\mathbf{m}}_{\mathbf{s}} - \hat{\mathbf{m}}_{\mathbf{x}}$. Our aim is to find the color transformation $\mathbf{s} = \mathbf{f}(\mathbf{x})$ from these sample data and, subsequently, apply it on the entire image. The *CIELAB* color space, which exhibits good correspondence between perceived and actual color differences, has been used. In the following, two methods for color restoration will be described.

2.1. Linear Approximation

A simple but effective choice for the transformation function is:

$$\mathbf{s} = \mathbf{f}(\mathbf{x}) = (\mathbf{A} + \mathbf{I})\mathbf{x} \tag{2}$$

where $\mathbf{I}$ is the 3×3 identity matrix and $\mathbf{A} = [\mathbf{a}_1\ \mathbf{a}_2\ \mathbf{a}_3]^T$ is a 3×3 coefficient matrix. The displacement vector $\mathbf{d} = \mathbf{s} - \mathbf{x}$ can be expressed as $\mathbf{d} = \mathbf{A}\mathbf{x}$. The coefficient matrix $\mathbf{A}$ can be computed by polynomial regression.

$$\left[\{\Delta\hat{\mathbf{m}}\}_{i1}\ \{\Delta\hat{\mathbf{m}}\}_{i2}\ \cdots\ \{\Delta\hat{\mathbf{m}}\}_{iN}\right]^T = \hat{\mathbf{m}}_{\mathbf{x}}^T \mathbf{a}_i \tag{3}$$

2.2. White Point Transformation

Another approach is based on the fact that an object may look different, under different lighting conditions. Therefore, we can assume that, if we illuminate a clean sample $\mathbf{s}$ with a "brownish" light source (characterized by its reference white $\mathbf{w}_{XYZ}$), we can obtain the dirty sample. Thus, the difference in appearance can be attributed solely to the different white points used for the CIEXYZ-to-CIELAB color transformation. Let $\mathbf{s}_{LAB}$ denote a vector of CIELAB values, which correspond to a clean sample, and let $\mathbf{x}_{XYZ}$ denote a vector that contains the tristimulus values of the corresponding oxidized sample.

For the restoration, a white point vector $\mathbf{w}_{XYZ}$ should be determined which should yield an estimate of the clean sample:

$$\hat{\mathbf{s}} = T\{\mathbf{x}_{XYZ}; \mathbf{w}_{XYZ}\} \tag{4}$$

where $T\{\cdot;\cdot\}$ denotes the nonlinear transformation from CIEXYZ to CIELAB. Given the sample mean vectors $\hat{\mathbf{m}}_{\mathbf{x}_{XYZ}}$ of the oxidized samples, the error can be expressed as:

$$\mathbf{e} = \hat{\mathbf{m}}_{\mathbf{s}} - T\{\hat{\mathbf{m}}_{\mathbf{x}_{XYZ}}; \mathbf{w}_{XYZ}\} \tag{5}$$

The instantaneous error function $\mathcal{E} = \mathrm{tr}(\mathbf{e}^T\mathbf{e})$ can be minimized with respect to $\mathbf{w}_{XYZ}$, to yield a solution for the white point vector using function minimization routines. Although this represents a sub-optimal solution, it can yield satisfactory results, with little computational overhead.

Subjective evaluation on a number of oxidized Byzantine icons indicated that satisfactory results can be obtained by both methods (Fig. 1). A more detailed description of these methods, along with other less efficient methods, can be found in [1].

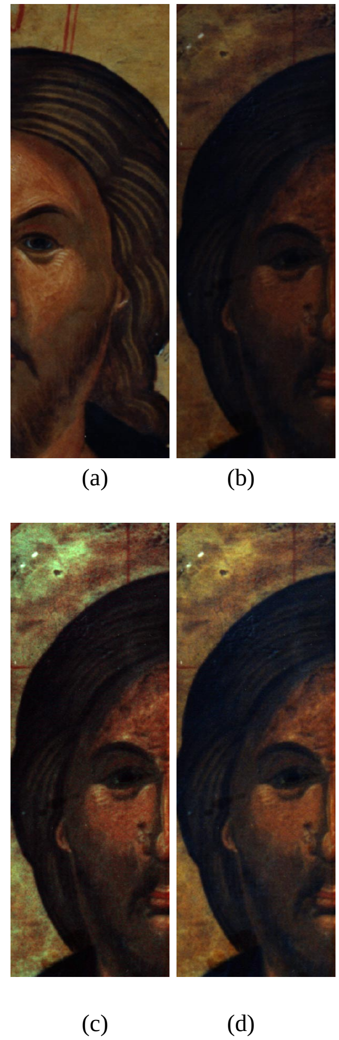


Fig. 1. (a) Clean and (b) oxidized region of the test image. Restoration results: (c) linear approximation and (d) white point transformation.

3. MOSAICING OF PAINTINGS ON CURVED SURFACES

In certain cases (murals painted in the interior of arches and vaults, paintings on the surface of cylindrical items, e.g. jars etc.) the surface where a painting is created is not flat but curved. In order to have a better understanding of such paintings for restoration purposes, it is sometimes preferable to unfold or flatten them to obtain a view of how they would have looked like, if they were painted on a planar surface. Since, in most cases, these paintings are of considerable dimensions, image capturing in partially overlapping parts is required in order to minimize geometry/perspective distortions and obtain efficient resolution. Subimages are subsequently synthesized to obtain the whole image, a procedure known as mosaicing.

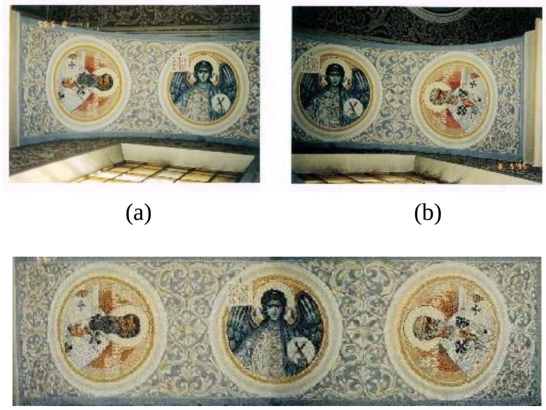
In order to proceed to the flattening of the acquired partial images, we have to know or estimate (a) the equation describing the painted cylindrical surface with respect to the object coordinate system, i.e., a system with one of its axes being the cylinder's revolution axis and (b) the transformation that relates coordinates in the camera coordinate system with coordinates in the object coordinate system. This transform is specified by a translation vector $\mathbf{t}$ and a rotation matrix $\mathbf{R}$.

The elements of $\mathbf{R}$ can be identified using information derived from two curves C_1^p, C_2^p on the image plane that are projections of two curves C_1, C_2 on the cylindrical surface that are drawn on intersections of the surface with planes perpendicular to its revolution axis. Identification of C_1^p, C_2^p in the image can be done interactively on an edge map of the image. Once these curves have been identified on the image an iterative procedure is used to find their common normal and subsequently, using geometry principles, the rotation matrix $\mathbf{R}$. If the translation vector $\mathbf{t}$ and the surface equation (e.g. the cylinder radius) are known, or can be estimated, the acquired image can be backprojected on the surface and subsequently flattened. Flattening results in an image where C_1^p, C_2^p are transformed to straight lines.

Due to the perspective projection, the flattened image is distorted. Arcs on the cylindrical surface having different length project to linear segments of equal length in the image plane. This distortion is bigger in the regions situated at the contact of the tangents from the viewpoint to the cylindrical surface (limb points). If images are to be mosaiced using an automatic procedure, the end parts of the image where large distortions occur should be considered unreliable for matching and, thus, excluded from the procedure. If one decides upon a maximum distortion threshold, the percentage of the image (at the two ends) where distortions exceed this threshold can be calculated. Furthermore, using this information, the minimum number of partial views that should be acquired in order the final mosaic image to have a certain distortion can be evaluated. Results of the procedures described above can be seen in Figure 2. Further details on the method can be found in [2, 3].

4. DIGITAL RESTORATION OF CRACKS

Many natural phenomena, like unfavorable weather conditions, cause frequently destructive effects on paintings. In dry environ-



(a) (b)

(c)

Fig. 2. (a),(b) Images depicting two parts of a painting on an arch; (c) Mosaicing of the flattened images.

(a) (b)

Fig. 3. (a) Original image; (b) Thresholded output of the top-hat transform.

ments, natural drying can lead to too rapid loss of water, resulting in non-uniform contraction and, eventually, in cracking. The digital crack restoration technique presented below consists of three stages: (a) detection of the cracks, (b) separation of the brush strokes which have been misidentified as cracks and (c) implementation of the crack filling procedure. A detailed description of the method can be found in [4].

4.1. Detection of the cracks

Cracks have usually low luminance and can be considered as being local minima with rather elongated structural characteristics. Crack detection can be achieved by applying the morphological top-hat transform [5] on the luminance image. This high-pass filter can detect bright details in an image $f(x)$:

$$y = f(x) - f_{nB}(x) \tag{6}$$

where $f_{nB}(x)$ is the opening of the function with the structuring set nB, defined as:

$$nB = B \oplus B \oplus \cdots \oplus B \qquad (n\ times) \tag{7}$$

The output of the top-hat transform contains only the luminance peaks in which the structuring element cannot fit and no background at all. Since cracks have usually small luminance, crack detection can be achieved by applying the top-hat transform on the negated luminance image. Control over the results of the crack detection can be obtained by modifying the type and the size of the structuring element and the number n in (7), which denotes how many times the operations of erosion and dilation will be applied.

The top-hat transform produces a grayscale output image $t(k, l)$. Therefore, a thresholding operation is required to separate cracks from the background. The results of the crack detection operation can be seen in Figure 3.

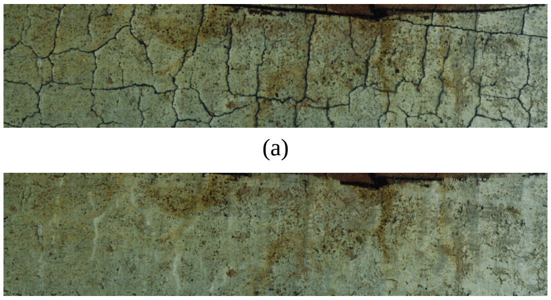
4.2. Separation of the brush strokes from the cracks

In some paintings, thin dark brush strokes exist (e.g. in hair), which have almost the same features (thickness, luminance) as cracks. Therefore, it is possible that the top-hat transform misclassifies these brush strokes as cracks. Thus, separation of these brush strokes from the actual cracks before the implementation of the crack filling procedure is necessary to prevent undesirable alterations to the image. Such a separation can be done on the basis of the hue and saturation values of the corresponding pixels. We have observed that the hue of the cracks in an image usually ranges from $0°$ to $60°$. On the contrary, the hue of the dark brush strokes varies in the whole gamut $[0°, 360°]$. Furthermore, crack saturation ranges usually from 0.3 to 0.7, while brush stroke saturation ranges from 0 to 0.4. Thus, on the basis of these differences, we can separate a great part of the dark brush strokes from cracks. This separation can be achieved by classification using median radial basis functions (MRBF) neural network, which is a robust version of radial basis functions (RBF) network [6]. The input vectors of the network consist of the hue and saturation values of pixels identified as cracks by the top hat transform. During the recall phase each input is assigned to one of the two available output classes (cracks and thin dark brush strokes).

4.3. Crack filling

After identifying cracks, our aim is to restore them by filling (interpolating) image information content within cracks. Interpolation should work only on pixels which belong to cracks and use local information (neighboring pixels).

An easy way to fill cracks is to apply median or related filters in the neighborhood of cracks. If the filter window is sufficiently large, the crack pixels are essentially outliers and can be rejected by order statistics filters. Thus, the crack pixels are assigned values equal to the median of the local observations, i.e., equal to one of the neighboring pixels. The median, weighted median and modified trimmed mean filters can be used for this purpose. Better results were obtained by using a filter that rejects all crack pixels within the filter window (identified by the thresholded output of the top-hat transform) and evaluating the mean or the median of the non-crack pixels in this window. However, the best restoration results were obtained by applying anisotropic diffusion [7] aiming at diffusing color/luminance information from the crack neighboring pixels to the actual crack pixels. A variant of the classical anisotropic diffusion technique that takes into account crack orientation was devised. Results of this crack filling technique are depicted in Figure 4.



(a)

(b)

Fig. 4. (a) Original image; (b) Crack filling using the modified anisotropic diffusion technique.

5. MULTIMODAL DIGITAL ARCHIVING OF PAINTINGS

Nowadays, museums and conservation centers rely heavily on database management systems (DBMS) for the efficient artwork-related information storage and retrieval. Although commercial database products do offer this level of functionality, they are not specialized to painting/artwork archiving. Such a system, tailored to the needs of archiving and cataloguing of paintings [8] is presented in this section. The system was developed using a relational database scheme that features a user friendly graphical user interface (GUI) that combines predefined queries and reports with user-defined SQL queries. Access to the database can be achieved through a client-server model with a specialized client application. A more powerful version that provides access to the database through any web browser is also available.

The selection of a record structure that satisfies archiving and conservation needs is a difficult task. The record structure developed within the European Union research project NARCISSE that dealt with digital representation of art-related information was the starting point for our implementation. However, this structure was modified to a certain extent in order to adapt it to the specific conservation needs of Byzantine icons.

A painting entity was created, that consists of more than forty attributes (fields) containing information on the following topics: physical details, restoration details, creation data, current physical conditions, storage information, historical data, artistic style, etc. Each painting entity can be associated with a number of other related entities that include bibliography, film, colorimetry measurements, digital images and spectroscopy signals.

For each painting, multimodal digital images resulting from different acquisition schemes (i.e., infrared, visible, x-ray, ultraviolet and microscopy) can be stored. Furthermore, the scheme supports image mosaicing (tiling) when an image is stored as a set of subimages (tiles) in order to increase the resolution. In this case, the relative position of each tile with respect to the entire painting is stored. Microscopy images are also supported. The relative position of the microscopy image with respect to the entire painting, is stored in the corresponding record. Storage of spectroscopy signals and colorimetry measurements is also supported. The spectroscopy signal entity includes fields that describe the spectroscopy type (e.g. Raman) and the absolute coordinates of the signal with respect to the image. The coordinate information can be used to display an image simultaneously with its signals. Colorimetry measurements can be stored similarly and displayed along with the image to which they refer to.

An example of the combined display capabilities of the system is presented in Figure 5, where a visible image is displayed along with a colorimetry measurement, a histogram and a xyY color space chart. Crosshairs in the image indicate points that have associated signals, measurements, or microscopy images. The respective color indicates the type of the associated data. By clicking on a crosshair symbol, which is associated with a signal, a graph of the respective signal data is displayed.

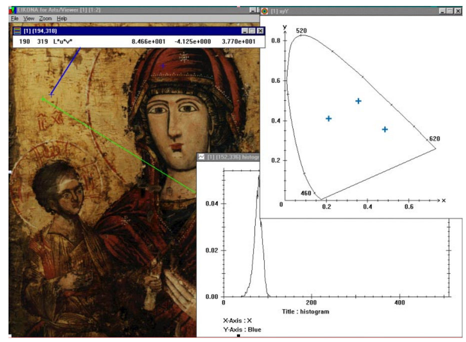


Fig. 5. Combined display of images, signals and colorimetry measurements.

6. REFERENCES

[1] M. Pappas and I. Pitas, "Digital Color Restoration of Old Paintings", *IEEE Trans. On Image Processing*, vol. 9, no. 2, pp. 291-294, February 2000.

[2] W. Puech, J.-M. Chassery and I. Pitas, "Cylindrical Surface Localization in Monocular Vision", *Pattern Recognition Letters*, vol. 18, no.8, pp. 711-722, August 1997.

[3] W. Puech, A. G. Bors, I. Pitas and J.-M. Chassery, "Projection distortion analysis for flattened image mosaicing from straight uniform generalized cylinders", to appear in *Pattern Recognition*, volume 34, Issue 8, August 2001.

[4] I. Giakoumis, I. Pitas, "Digital Restoration of Painting Cracks", *IEEE Int. Symposium on Circuits and Systems (ISCAS'98)*, California, USA, June 1998 (CDROM Proceedings).

[5] I. Pitas and A.N. Venetsanopoulos, *Nonlinear Digital Filters, principles and applications.* Norwell, Kluwer Academic, 1990.

[6] A. G. Bors and I. Pitas, "Median Radial Basis Function Neural Network", *IEEE Trans. on Neural Networks*, vol. 7, no.6, pp. 1351-1364, November 1996.

[7] P. Perona, J. Malik, "Scale-Space and Edge Detection using anisotropic diffusion," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 12, no. 7, pp. 629–639, July 1990.

[8] M. Pappas, G. Angelopoulos, A. Kadoglou and I. Pitas, "A Database Management System for Digital Archiving of Paintings and Works of Art", *Computers and the History of Art*, vol. 8, no. 2, pp. 15-35, 1999.