Old painting digital color restoration

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Abstract

Many old paintings suffer from the effects of certain physicochemical phenomena, that can seriously degrade their overall visual appearance.Digital image processing techniques can be utilized for the purpose of restoring the original appearance of a painting, with minimal physical interaction with the painting surface. In this paper, a number of methods are presented which can yield satisfactory results. Indeed, simulation results indicate that acceptable restoration performance may be attained, despite the small size of painting surface data utilized.

1 Introduction

Varnish oxidation is a phenomenon that can degrade seriously the overall visual appearance of old paintings. The process of removing this oxidation layer is performed by conservation experts. It is a time-consuming process which does not always promise guaranteed success. Indeed, the prevailing environmental conditions as well as the chemical properties, which are exhibited by the wide spectrum of different varnishes, make the task of selecting the appropriate cleaning process quite difficult.

Digital image processing techniques can be applied for color restoration, aiming at obtaining an estimate of the original appearance of a painting, without extensive chemical cleaning treatment of its surface. In this context, Volterra filters have been utilized to extract the original color information, by utilizing sampled images, in the RGB color space, of certain regions of the painting, before and after cleaning [1].

Since the RGB color space does not possess perceptional uniformity, other color spaces might be more appropriate, at least for the purposes of color image processing applications. The *CIELAB* color space exhibits good correspondence between perceived and actual color differences, with the added advantage of device-independence [2].

Some novel approaches to this problem are presented in this paper. Only one acquisition pass is required, provided that a number of painting patches have already been cleaned. In addition to uniform chromaticity, these samples should be representative of the colors that appear in the painting. Finally, similar colors to the ones of these clean samples should also exist in oxidized parts of the painting.

The rest of this paper is as follows. In Section 2 the mathematical foundation of the restoration methods is given. Experimental results are presented in

Section 3. Finally, some conclusions regarding the overall restoration performance are presented in Section 4.

2 Restoration approaches

The problem can be stated as follows. Let us suppose that $\mathbf{s}$ is the original image (unknown) and $\mathbf{x} = \mathbf{g}(\mathbf{s}) + \mathbf{n}$ is the degraded (oxidized) one, where $\mathbf{g}(\cdot)$ denotes the unknown degradation function and $\mathbf{n}$ is observation noise. Let us suppose that we have N cleaned and degraded color samples $\mathbf{x}_i,\ \mathbf{s}_i$ respectively, with $i = 1, \ldots, N$. The problem is to perform a "blind" estimation $\hat{\mathbf{s}}$ of the inverse function $\hat{\mathbf{s}} = \mathbf{f}(\mathbf{x})$, based on these measurements that minimize the following approximate expression for the mean square error (MSE):

$$MSE \simeq \frac{1}{N}\sum_{n=1}^{N} ||\mathbf{s}_n - \hat{\mathbf{s}}_n||^2 = \frac{1}{N}\sum_{n=1}^{N}(\mathbf{s}_n - \hat{\mathbf{s}}_n)^T(\mathbf{s}_n - \hat{\mathbf{s}}_n) \tag{1}$$

As it has already been mentioned above, this approach deviates from standard restoration procedures, because the degradation function is unknown. Despite the involvement of some first-order statistics, the problem is approached clearly from a deterministic point of view. That is, little or no assumptions are made about the painting surface degradation model.

In the following, the goal is the derivation of a function that can describe adequately the change in chrominance and luminance of the painting surface. It should be clear that limited spatial information will be utilized in order to approximate this phenomenon.

2.1 Linear approximation

Assume that the color of a pixel is denoted by $\mathbf{x} = [x_1\ x_2\ x_3]^T$, where $x_1,\ x_2$ and x_3 correspond to the $L^*,\ a^*$ and b^* color space coordinates of the point, respectively. If N cleaned regions are available, N corresponding regions from the oxidized part of the image should be selected. Let the vectors $\hat{\mathbf{m}}_{\mathbf{s}_i}$ and $\hat{\mathbf{m}}_{\mathbf{x}_i}$, with $i = 1, \ldots, N$, represent the sample mean of the ith clean and oxidized region, respectively. For each degraded observation $\mathbf{x}$ we are interested in obtaining an estimate $\hat{\mathbf{s}} = \mathbf{f}(\mathbf{x})$ of the reference color $\mathbf{s}$. A possible choice for this function is:

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

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 $\mathbf{d} = \mathbf{A}\mathbf{x}$, while the coefficient matrix $\mathbf{A}$ can be computed by polynomial regression, that is $[d_{1i}\ d_{2i}\ \cdots\ d_{Ni}]^T = \hat{\mathbf{m}}_{\mathbf{x}}^T\mathbf{a}_i$ where $d_{ij} = \hat{m}_{\mathbf{s}_{ji}} - \hat{m}_{\mathbf{x}_{ji}}$ and:

$$\begin{aligned} \hat{\mathbf{m}}_{\mathbf{s}} &= [\hat{\mathbf{m}}_{\mathbf{s}_1}\quad \hat{\mathbf{m}}_{\mathbf{s}_2}\quad \cdots\quad \hat{\mathbf{m}}_{\mathbf{s}_N}] \\ \hat{\mathbf{m}}_{\mathbf{x}} &= [\hat{\mathbf{m}}_{\mathbf{x}_1}\quad \hat{\mathbf{m}}_{\mathbf{x}_2}\quad \cdots\quad \hat{\mathbf{m}}_{\mathbf{x}_N}] \end{aligned} \tag{3}$$

2.2 White point transformation

Another approach is based on the fact that an object may look different, under different lighting conditions [3]. Assume that a clean sample and its oxidized version are viewed under the same lighting conditions. Different *CIEXYZ* (and, consequently, CIELAB) values would be recorded. Instead of trying to produce an estimate of the color difference for corresponding clean and oxidized samples, an assumption can be made that both of the samples have similar CIEXYZ values. Thus, the difference in appearance can be attributed solely to the different white points used for the color transformation required to obtain CIELAB values. In the discussion that follows, vectors with the index XYZ refer to CIEXYZ tristimulus values. Let $\mathbf{s}$ 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. The mapping from one color space to the other is given by a nonlinear equation of the form:

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

where $T\{\cdot;\cdot\}$ denotes the nonlinear transformation from CIEXYZ to CIELAB and $\mathbf{w}_{XYZ}$ is the white point tristimulus values vector. Thus, a white point vector $\mathbf{w}_{XYZ}$ should be determined which, after being substituted into equation (4), should yield an estimate $\hat{\mathbf{s}} = T\{\mathbf{x}_{XYZ}; \mathbf{w}_{XYZ}\}$ of the clean sample. Given the sample mean vectors $\hat{\mathbf{m}}_{\mathbf{x}_{XYZ}}$ of the oxidized samples, the error can be expressed as:

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

Since the mean square error $E[\mathbf{e}^T\mathbf{e}]$ can not be estimated, 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. Although this is a sub-optimal solution, it can yield satisfactory results, with little computational overhead and is extensively used in calibration problems [2].

2.3 RBF approximation

Radial basis functions networks have been used successfully as universal function approximators [4]. An arbitrary mapping $f : \mathcal{R}^p \Rightarrow \mathcal{R}$ can be approximated as follows:

$$f(\mathbf{x}) \simeq \sum_{m=1}^{M} w_m \phi(||\mathbf{x} - \mathbf{t}_m||) \tag{6}$$

where $\{\phi(||\mathbf{x} - \mathbf{t}_m||)|m = 1, \ldots, M\}$ is a set of M arbitrary functions, which are known as *radial basis functions*, with corresponding centers $\mathbf{t}_m$ and weights w_m. Of course, if the unknown function is a mapping of the form $f : \mathcal{R}^p \Rightarrow \mathcal{R}^q$, equation (6) can be utilized to perform approximation on each one of the q dimensions separately.

Let $\phi(\cdot)$ denote the non-normalized Gaussian function, i.e.:

$$\phi(||\mathbf{x} - \mathbf{t}_m||) = g(\mathbf{x}; \mathbf{t}_m, \mathbf{\Sigma}_m^{-1}) \tag{7}$$

where $\mathbf{\Sigma}_m^{-1}$ represents the inverse covariance matrix of the mth Gaussian and:

$$g(\mathbf{x}; \mathbf{t}_m, \mathbf{\Sigma}_m^{-1}) = \exp\left\{-\frac{1}{2}(\mathbf{x}-\mathbf{t}_m)^T \mathbf{\Sigma}_m^{-1}(\mathbf{x}-\mathbf{t}_m)\right\} \tag{8}$$

Our goal, is the RBF approximation of the unknown function $\mathbf{f} : \mathcal{R}^3 \Rightarrow \mathcal{R}^3$, where it is known that:

$$\mathbf{f}(\hat{\mathbf{m}}_{\mathbf{x}_n}) = \hat{\mathbf{m}}_{\mathbf{s}_n} - \hat{\mathbf{m}}_{\mathbf{x}_n},\ n = 1, \ldots, N \tag{9}$$

The function $\mathbf{f}$ can also be written as: $\mathbf{f}(\mathbf{x}) = [f^{(1)}(\mathbf{x}) \quad f^{(2)}(\mathbf{x}) \quad f^{(3)}(\mathbf{x})]^T$, where $f^{(i)},\ i = 1, 2, 3$ is the ith color component of $\mathbf{f}$. Thus:

$$f^{(i)}(\mathbf{x}) \simeq \sum_{m=1}^{M} w_m^{(i)} g(\mathbf{x}; \mathbf{t}_m^{(i)}, \mathbf{\Sigma}_m^{(i)^{-1}}),\ i = 1, 2, 3 \tag{10}$$

where the parameters of M Gaussian functions should be estimated, for each one of the three color components. Estimation was carried out by a gradient descent algorithm, in order to minimize the total squared error [4]. If the data set size N is large, the computational requirements can be greatly reduced, if the covariance matrix assumes a diagonal for, although this may limit the overall network restoration performance.

3 Simulation results

Simulations were carried out on a painting which was chemically cleaned on its right half. Regions of the cleaned and oxidized parts are depicted in Figures 1(a) and (b), respectively. Five regions on each part were selected, with sizes ranging from 5×5 to 16×16 points, depending on the uniformity of the sample. Sample mean values of each region were estimated and consequently utilized to restore the oxidized image, with the methods described in Section 2.

Results of the linear approximation and white point transformation methods are shown in Figures 1(c) and (d), respectively. In the RBF approach either one or two Gaussians per color channel were used to approximate the displacement in the CIELAB color space. An estimate of the mean square error $E[(\hat{\mathbf{m}}_{\mathbf{s}} - \hat{\mathbf{m}}_{\hat{\mathbf{s}}})^T(\hat{\mathbf{m}}_{\mathbf{s}} - \hat{\mathbf{m}}_{\hat{\mathbf{s}}})]$ was used as a quantitative criterion for assessing color restoration performance. Results are summarized in Table 1. Subjective comparison indicated satisfactory performance, for the white point and linear approximation methods, with the former slightly outperforming the latter, as can be seen by comparing Fig. 1(c)-(d) with Fig. 1(a).

The fact that, subjectively, restoration performance does not correlate well with the figures of Table 1 is not at variance with the claim of good perceptual uniformity of the CIELAB color space.Indeed, the RBF networks used approximated quite well the unknown function at the points of the data set, but could not interpolate satisfactorily. This is a consequence of the small data set size used in this experiment. White point transformation and linear approximation yielded good approximation and interpolation performance, due to the

Table 1: Comparison of MSE for the presented methods.

Method	*MSE*
Linear approximation	93.21
White point	190.37
RBF (one Gaussian per channel)	126.46
RBF (two Gaussians per channel)	88.30

underlying "smoothing" nature of each method. Additionally, computational requirements of these two methods is low.

The effectiveness of the presented methods, was found to be strongly dependent on the size of the data used, as well as the size of the color space region they occupied. Of these two factors, the latter one is of the highest significance, because if the gamut covered by the available samples is very limited, poor restoration performance will be obtained, regardless of the number of samples used.

4 Conclusions

This paper presented a number of digital restoration techniques for old paintings, which can be used to recover the original painting appearance with little physical manipulation of the painting surface. Despite the apparent simplicity of these methods, simulations performed on a number of different paintings indicated that satisfactory results can be obtained. In addition to the advantages mentioned above, the small computational requirements can contribute to the overall usefulness of these methods.

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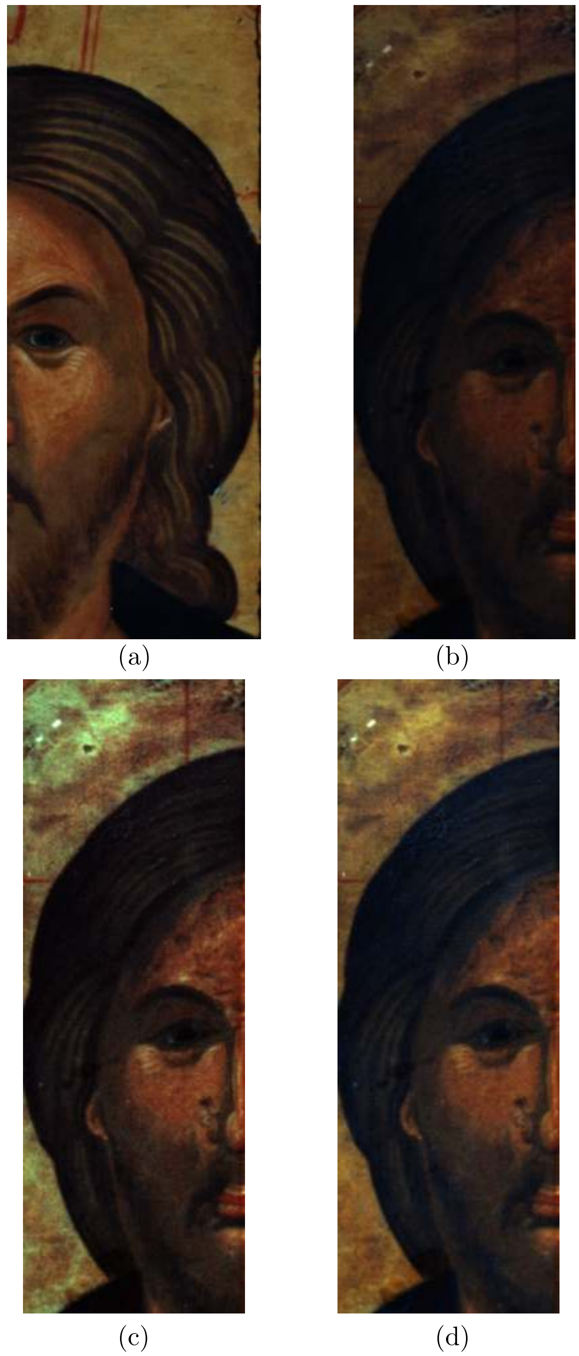

Figure 1: (a) Clean and (b) oxidized region of the test image. Restoration performance results: (c) linear approximation and (d) white point transformation.