Digital Restoration of Old Paintings

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ABSTRACT

Paintings are made up of materials that can suffer damage with the passage of time. To protect them over a long period, they are coated with a protecting covering of varnish layer. The varnish layer over paintings is affected by atmospheric conditions, fluctuations in temperatures, humidity and sunlight. Over a period of time, the transparency of the varnish becomes clouded and discolored, often resulting in a picture being viewed as if through an amber or even brown or black filter. We analyze the effect of varnish layer on the visual appearance of old paintings and provide the correlation of degradation with the quantitative measures such as entropy and standard deviation of the points cluster of the image in the color space. We further develop a method of color restoration by appropriately transforming the color space. We provide both an interactive method and an automated example-based method. In addition to the color degradation, cracks which appear apparently on the surface, are also caused by the aging process. As a result of cracks and color degradation, paintings may lose their aesthetic and historical values. In this paper, we also integrate crack detection with color restoration.

Keywords

color restoration, crack detection, crack filling, inpainting, crack restoration.

1 INTRODUCTION

Digital image processing techniques are widely used in all scientific fields. Image processing techniques are recently being applied to analyze, preserve and restore artwork. Art work restoration is a very demanding field which requires considerable expertise. As the years roll by, a number of defects appear in paintings like the development of cracks, scratches, discoloration of the varnish layer, accumulation of dust, dirt, smoke on the surface of the painting, loss of paint, etc. Hence, the restoration of such old degraded paintings include stabilization, surface cleaning, the removal of discolored varnish, the repair of tears and punctures, filling areas of paint loss, and expert retouching. Digital processing on the old paintings is analogous to this manual, chemical cleaning of old paintings. Hence, art conservators and restorators can be helped using such digital image processing techniques.

In this paper, we present an approach for restoration of digital paintings inspired by the manual process for cleaning and color restoration of old paintings which may have undergone a degradation in their visual appearance due to the accumulation of dirt, smoke and oxidation of the varnish layer (in oil paintings) etc.
The paper is organized as follows. In section 2, some of the vital previous research carried out in this field is discussed along with our contribution. Section 3 analyses the effect of the varnish layer on the color space of old paintings. Section 4 describes the similarity metric chosen to assess the quality of results and the procedure adopted to quantitatively compare the results. Section 5 describes the role and purpose of user intervention in the process of digital color restoration. In section 6, we present another approach for digital color restoration of old paintings based on example clean paintings. Section 7 presents some of the results followed by section 8 which concludes our work.

2 RELATED WORK

Pappas & Pitas [PP00] report a pioneering work on digital color restoration of old paintings. They mention five approaches for cleaning an image. In each of these, they try to derive a color transformation f such that $s = f(x)$ using cleaned samples (denoted by s) and old samples (denoted by x) of the painting. Linear Approximation and White Point transformation approaches yield promising results as compared to other three approaches. Palomero & Soriano [PS11] propose a method which uses a neural network to learn the transformation from dirty to clean segments of a painting image. Gasparini and Schettini [GS03] suggest an algorithm which is structured in two main parts: a cast detector and a cast remover. An acquired image may have a cast which is an undesirable shift in the entire color range. Reinhard et al. [RA01] use a simple statistical analysis to impose one image's color characteristics on another. They achieve color correction by choosing an appropriate source image and apply its characteristic to another image.

Giakoumis & Pitas [GP98] propose a method for digital restoration of cracks in old paintings. The technique consists of the following steps:

- Detection of cracks using the top hat transformation.
- Separation of brush strokes which have been misidentified as cracks.
- Crack filling procedure using seed growing approach.

Separation of brush strokes is achieved by classification using Minimal Radial Basis Function (MRBF) neural network. Therefore, a huge number of samples of cracks and brush strokes are required for the learning stage. The Minimal Radial Basis Function (MRBF) neural network [ZV09], after its training phase, becomes capable of deciding whether the pixel area in the original image belongs to a brush stroke or a crack. Crack filling is performed using the Bertalmio et al.'s inpainting [BS00] and Exemplar based inpainting technique [CP04].

Contribution: In this paper, we analyze the role of oxidized varnish layers on the color space of old paintings and on their appearance. We also propose an approach for digital color restoration without performing any chemical treatment on the surface of the painting. We provide an interactive method to modify the color space, represented as point clusters of RGB. Further, we introduce an example-based technique to automatically transform the RGB space of the given degraded image in accordance to an example image. We provide a quantitative measure of KL-divergence (relative entropy) to support the results.

3 ANALYSIS OF VARNISH LAYER

The varnish layer protects the painting from abrasion and pollution in the atmosphere. It also brings out the colors to the brilliance they had when applied while it is still transparent, but over a period of time, due to oxidation and deposition of dirt and smoke, the varnish layer becomes opaque, resulting in a picture being viewed as if through an amber or even brown or black filter.

In Figure 1 we can observe that, overlapping area has dull and amber look as compared to other region of the painting. On experimenting with a number of paintings, it has been observed that due to the dirty varnish layer, the standard deviation and entropy of the image

Figure 1: Effect of dirty varnish layer

decreases. Tables 1, 2 & 3 exhibit the comparison of the results of standard deviation and entropy of a number of chemically cleaned and old paintings.

They represent the point cluster of old and chemically cleaned paintings in RGB color space. It is observed that due to the effect of oxidized varnish layer the mean color ($\bar{R}$, $\bar{G}$ and $\bar{B}$) changes and subsequently results in shifting the origin of the point cluster of the paintings.

It is also observed that the point cluster volume of the old painting also decreased (due to decrease in the standard deviation). Further, due to decreased point cluster volume, only limited range of colors is available to represent the image giving it an amber coloration and hiding the vibrant colors beneath.

Poor contrast images have a dull look due to the low range of gray levels available for the image and we can improve their appearance by increasing the range of gray levels (histogram stretching). We observe that transformations such as scaling, translation and rotation must have been applied on the point cluster of old painting to obtain the point cluster of the chemically cleaned painting. The point clusters could be obtained in either RGB or $L\alpha\beta$ color space. Thus, we utilize this concept of applying the various transformations on the given point cluster of the old painting and observe its corresponding effect on the painting. Now, in the next section, we show user intervention in specifying the various parameters for scaling and translation and obtain a satisfactorily clean image based on the visual perception.

4 SIMILARITY METRIC

Many image quality assessment(QA) algorithms exist in the literature whose goal is to automatically assess the quality of images in a perceptually consistent manner. These image QA algorithms [SB05, SB06, ZJ06, WS05, WL11, MS01] interpret image quality as fidelity or similarity with a 'reference' or a 'perfect' image. Wang and Simoncelli [WS05] predict the visual quality of distorted images using only the partial information about the reference images. They propose QA

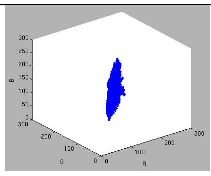
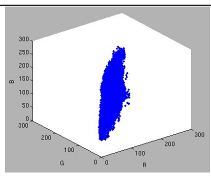
Image	Point cluster	Red Mean	Red Std. Dev.	Red Entropy	Green Mean	Green Std. Dev.	Green Entropy	Blue Mean	Blue Std. Dev.	Blue Entropy
		184.6	20.8	6.032	182.2	19.5	5.825	144	22.7	5.983
		155.9	54.1	7.386	158.2	54.3	7.287	158.0	66.3	7.278

Table 1: Statistics of a pair of degraded and clean paintings

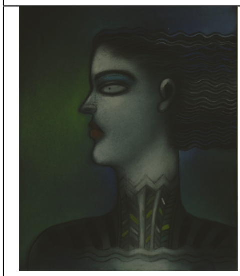
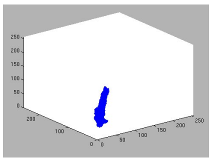
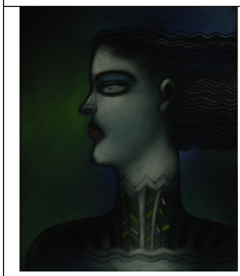
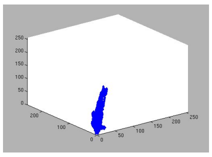
Image	Point cluster	Red Mean	Red Std. Dev.	Red Entropy	Green Mean	Green Std. Dev.	Green Entropy	Blue Mean	Blue Std. Dev.	Blue Entropy
		44.2	13.2	4.818	48.4	15.4	5.424	40.1	13.5	5.095
		21.1	16.8	5.136	27.2	19.5	5.754	23.6	17.1	5.423

Table 2: Statistics of a pair of degraded and clean paintings

method in the wavelet transform domain. They use the Kullback-Leibler(KL) distance [S07, CT91] between the marginal probability distributions of wavelet coefficients of the reference and distorted images as a measure of image distortion. We use KL-divergence values to find out the relative entropy between two color distributions. In order to assess if the new sample painting has similar color distribution to the old panting, we first perform eigen-space transformation followed by KL-divergence calculation. The Kullback-Leibler divergence (also information divergence, relative entropy) is a non-symmetric measure of the difference between two probability distributions P and Q. KL measures the expected number of extra bits required to code samples from P when using a code based on Q, rather than using a code based on P. Typically P represents the "true" distribution of data, observations. The measure Q typically represents an approximation of P.

$$D_{KL}(P||Q) = \sum_i P(i)\ ln \frac{P(i)}{Q(i)}$$

In our approach, we calculate the mean of pixel data along the three axes and compute the covariance matrices between the three components in the color space for both the given old and sample painting. Then, we decompose the covariance matrix using SVD algorithm and obtain the rotation and scaling matrices. Corresponding eigenvalues and eigenvectors are obtained from the covariance matrix. The point clusters of the image is translated to the origin by subtracting the mean obtained along the three reference axes. Eigenvectors are aligned with the reference axis by applying the rotation matrix on all the pixels of the image. Hence, the eigen-vectors of both the old and sample painting are now, aligned with the standard R, G and B axes. Now, we find the KL-divergence values between these transformed distributions. Low values of KL-divergence jus-

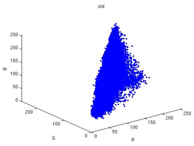
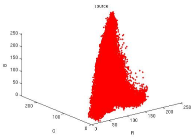
Image	Point cluster	Red Mean	Red Std. Dev.	Red Entropy	Green Mean	Green Std. Dev.	Green Entropy	Blue Mean	Blue Std. Dev.	Blue Entropy
		156.8	40.5	7.332	132.9	38.5	7.281	112.7	34.2	7.105
		156.6	45.8	7.505	138.2	48.5	7.604	126.9	51.5	7.633

Table 3: Statistics of a pair of degraded and clean paintings

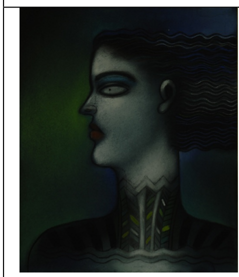
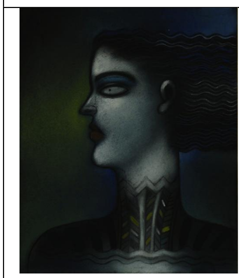
Image	Red Entropy	Green Entropy	Blue Entropy	KL-divergence
	5.136	5.754	5.423	0.43
	5.274	5.812	5.438	0.48

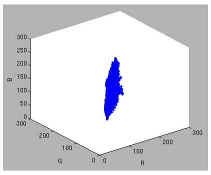
Table 4: Statistics of a pair of manually cleaned and restored paintings

tify the visual similarity of the distributions. Table 4 exhibits the comparison of the values of entropy and KL-divergence of manually cleaned painting and restored painting.

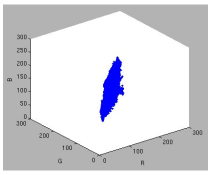
5 USER INTERVENTION IN DIGITAL COLOR RESTORATION

In this section, we incorporate the user interaction in our system. In this way, the user can interactively alter the distribution of the image (point cluster formed by all the pixels of the image in the Red, Green and Blue dimensions) by performing the various operations of rotation, scaling or translation. We use the following approach: we compute the mean for the old image in RGB space. We subtract the mean from all the data points as a result of which, the entire point cluster shifts to the origin. Then, user can scale the data points in all the three dimensions based on his visual perception of the corresponding impact on the painting. Next, we add the averages that we previously subtracted. Hence, the point cluster has now again been shifted to the original mean.

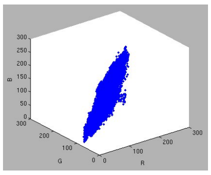
Figure 2 illustrates the above mentioned technique. Figure 2(a) and Figure 2(b) represent the old painting along with its corresponding point cluster. In Figure 2(d), scaling factors are scaled by 1.11 in the Blue dimension, 1.04 in the Green dimension and 1.07 in the Red dimension, Figure 2(c) shows the corresponding effect on the image. Similarly, in Figure 2(e), scaling in the Red dimension is done by a factor of 1.12. In Figure 2(g), further scaling factor of 1.10 in the Green dimension is applied. In Figure 2(i), the Blue dimension is scaled by 1.14. Further, the values in the R, G and B dimensions are normalized in the interval [0:1]. Figure 2(k) is the painting with satisfactory cleaning and Figure 2(j) is its corresponding point cluster. In supplement material, we have included more such examples. Basically, we increase the range of gray levels by performing scaling and translation. In the same way, we try to stretch the range of colors by matching the color spaces of the two paintings to give it a cleaned appearance.

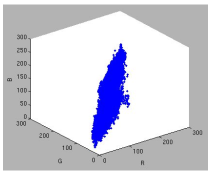
(a) Original painting (b) Point cluster of (a)

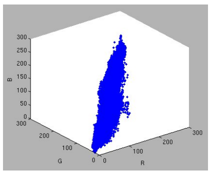
(c) (d)

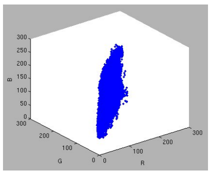
(e) (f)

(g) (h)

(i) (j)

(k) (l) Point cluster of (k)

Figure 2: Paintings and their corresponding point cluster obtained after interactively tweaking the scaling factors in the three R,G,B dimensions.

6 EXAMPLE-BASED DIGITAL COLOR RESTORATION APPROACH

In this section, we present how to match the color space of two paintings to give clean appearance to the old painting using a statistics based method [XM06].

First, calculate the mean of pixel data along all three axes R, G and B for both the old and sample cleaned painting, denoted as $(\bar{R}_{\text{old}}, \bar{G}_{\text{old}}, \bar{B}_{\text{old}})$ and $(\bar{R}_{\text{clean}}, \bar{B}_{\text{clean}}, \bar{G}_{\text{clean}})$ respectively.

Then calculate the covariance matrices for both the paintings Cov_{old} and $\text{Cov}_{\text{clean}}$

$$Cov = \begin{pmatrix} cov(R,R) & cov(R,G) & cov(R,B) \\ cov(R,G) & cov(G,G) & cov(G,B) \\ cov(R,B) & cov(G,B) & cov(B,B) \end{pmatrix}$$

Now, decompose the covariance matrix using singular value decomposition to get U and S which are required to derive rotation & scaling matrices.

$$Cov = U * S * V^{\mathrm{T}}$$

where U and V are unitary matrices and are composed of eigenvectors of covariance matrix, S is a diagonal matrix of eigenvalues of Cov. $S = diag(\lambda^{\mathrm{R}}, \lambda^{\mathrm{G}}, \lambda^{\mathrm{B}})$

Translation matrices

$$T_{\text{old}} = \begin{pmatrix} 1 & 0 & 0 & \bar{R}_{\text{old}} \\ 0 & 1 & 0 & \bar{G}_{\text{old}} \\ 0 & 0 & 1 & \bar{B}_{\text{old}} \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

$$T_{\text{clean}} = \begin{pmatrix} 1 & 0 & 0 & \bar{R}_{\text{clean}} \\ 0 & 1 & 0 & \bar{G}_{\text{clean}} \\ 0 & 0 & 1 & \bar{B}_{\text{clean}} \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

Rotation matrices

$$R_{\text{old}} = U_{\text{old}}, R_{\text{clean}} = U_{clean}^{-1}$$

Scaling matrices

$$S_{\text{old}} = \begin{pmatrix} \lambda_{old}^{R} & 0 & 0 & 0 \\ 0 & \lambda_{old}^{G} & 0 & 0 \\ 0 & 0 & \lambda_{old}^{B} & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

$$S_{\text{clean}} = \begin{pmatrix} s_{clean}^{R} & 0 & 0 & 0 \\ 0 & s_{clean}^{G} & 0 & 0 \\ 0 & 0 & s_{clean}^{B} & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

where $s_{clean}^{R} = 1/\sqrt{\lambda_{clean}^{R}}$, $s_{clean}^{G} = 1/\sqrt{\lambda_{clean}^{G}}$, $s_{clean}^{B} = 1/\sqrt{\lambda_{clean}^{B}}$

The final transformation will have the following form:

$$I = T_{clean}.R_{clean}.S_{clean}.S_{old}.R_{old}.T_{old}.I_{old}$$

where $I = (R, G, B, 1)^{T}$ and $I_{tgt} = (R_{tgt}, G_{tgt}, B_{tgt}, 1)^{T}$ denote the homogeneous coordinates of pixel points for the result and old paintings respectively. This transformation is applied to each pixel of the old painting.

We generate the results in $l\alpha\beta$ color space as well. $l\alpha\beta$ color space [RC98] minimizes correlation between channels for many natural scenes. This space is based on data-driven human perception research that assumes the human visual system is ideally suited for processing natural scenes. There is little correlation between the axes in $l\alpha\beta$ space, which lets us apply different operations in different color channels with some confidence that undesirable cross-channel artifacts won't occur. Additionally, this color space is logarithmic, which means to a first approximation that uniform changes in channel intensity tend to be equally detectable. We follow the following approach: the old painting is converted from RGB to $l\alpha\beta$ space. Then, we compute the mean and standard deviation for both the old and sample clean painting in l$\alpha\beta$ space. We subtract the mean from the data points:

$$l^* = l - \langle l \rangle$$
$$\alpha^* = \alpha - \langle \alpha \rangle$$
$$\beta^* = \beta - \langle \beta \rangle$$

Then, we scale the data points comprising the old image by factors determined by the respective standard deviations:

$$l' = \frac{\sigma_t^l}{\sigma_s^l} l^*$$
$$\alpha' = \frac{\sigma_t^\alpha}{\sigma_s^\alpha} \alpha^*$$
$$\beta' = \frac{\sigma_t^\beta}{\sigma_s^\beta} \beta^*$$

where $\sigma_t^l, \sigma_t^\alpha$ and σ_t^β are the standard deviations for the sample clean painting in l, α, β dimensions respectively, and $\sigma_s^l, \sigma_s^\alpha$ and σ_s^β are the standard deviations for the old painting in l, α, β dimensions respectively. After this transformation, the resulting data points have standard deviations that conform to the sample clean painting. Next, instead of adding the averages that we previously subtracted, we add the averages computed for the sample clean painting. Finally, we convert the result back to RGB color space.

As discussed earlier, for changing the appearance of an old painting to a cleaned one, we have to match its color point's cluster to another sample cleaned painting, which has the similar color distribution as the old painting. All in all, these transformations simulate morphing an ellipsoid to fit another one. The center coordinates of an ellipsoid is the mean, and the eigenvectors and eigenvalues of the covariance matrix indicate the directions and length of the three axes of the ellipsoid. In order to assess if the new sample painting has the similar color distribution as the old panting, we perform eigen-space transformation followed by KL-divergence. Table 5 lists the KL-divergence values between the histograms plotted in the 3 dimensions (red, green, blue) for the transformed old painting and the sample painting. Values are obtained for the two test cases. The relative entropy between the old and sample paintings is quite low, this observation justifies the visual similarity of the color distribution of the sample and the old painting.

Channels	Fig3(c)(KL-divergence	Fig3(g)(KL-divergence)	Fig3(k)(KL-divergence
Red channel	0.57	0.41	0.31
Green channel	1.43	0.52	0.74
Blue channel	1.51	1.87	0.36

Table 5: KL-divergence values for the old painting and the chosen sample paintings for Fig 3

Channels	Fig4(b)(KL-divergence)	Fig4(d)(KL-divergence)
Red channel	0.43	0.48
Green channel	1.90	1.91
Blue channel	0.37	0.94

Table 6: KL-divergence values for the manually cleaned painting and the restored painting with reference to old painting for Fig 4

Channels	Fig5(b)(KL-divergence)	Fig5(d)(KL-divergence)
Red channel	0.18	0.38
Green channel	0.15	0.62
Blue channel	0.50	0.81

Table 7: KL-divergence values for the manually cleaned painting and the restored painting with reference to old painting for Fig 5

Channels	Fig7(b)(KL-divergence)	Fig7(d)(KL-divergence)
Red channel	0.17	0.08
Green channel	0.24	0.21
Blue channel	0.28	0.13

Table 8: KL-divergence values for the manually cleaned and the restored painting with respect to the old painting for Fig 7

Figure 3 demonstrates the use of different sample paintings to restore an old painting. A different kind of look and feel is imposed on the old painting depending upon the sample painting chosen. In Figures 4, 5 & 7, an old painting is cleaned using an example clean painting having similar color distribution as that of the old painting. Figure 6 shows a painting partially cleaned using chemicals. The remaining old part is cleaned using the sample painting taken from the cleaned part of the old painting itself for color restoration. The result is shown in (c) which is comparable to the chemically cleaned part. Again, for the purpose of numerical analysis, we adopt the same technique of eigen-space transformation followed by KL-divergence as described above. Tables 6, 7 & 8 lists the KL-divergence values between the histograms plotted in the 3 dimensions (red, green, blue) for the manually cleaned painting and restored painting with reference to the old painting. Since, the values for the example1 painting is the minimum, it supports that its color distribution would correspond most closely to the candidate painting. Thus, it is chosen for the cleaning of the old painting.

7 RESULTS

In order to assess the quality of the color restored images, we apply the above mentioned technique for color restoration on 25 old and oxidized paintings. Evaluation is done by comparing the restoration results with the chemically cleaned paintings. The technique generates comparable results to chemically cleaned paintings depending upon the similarity in color distribution of old and sample cleaned painting. We compare the results generated by our algorithm with the ground truth (chemically cleaned images). Based on the similarity between the color distributions of the ground truth and the chemically cleaned paintings, we infer that our results are visually comparable with the ground truth. We have also incorporated crack restoration. Several efforts have been made in this field of crack restoration [SS10, PS11, GW08, GP98, BS00, OB01, T04, CP04, BB00]. The crack restoration technique consists of the following stages: crack detection and crack filling. Cracks can be detected using various techniques such as top-hat transformation (morphological filter) [SS10], [PS11], thresholding operation or techniques involving user-intervention [GW08]. Cracks can be filled using anisotropic diffusion [GP98], Bertalmio et al's inpainting technique [BS00], Oliveira et al's technique [OB01], Fast Marching Method (FMM) [T04], Exemplar based approach [CP04], Barni et al's crack filling technique[BB00]. We integrate crack detection with color restoration. Figure 8 depicts the original painting which requires both color restoration and crack filling. Initially, the colors of the painting are restored using the above mentioned example-based color restoration approach followed by crack filling using exemplar-based inpainting. Crack restoration results are depicted in Figures 9 & 10. In our approach, cracks are detected using top-hat transformation (disk as a structuring element) and a mask is created. Then, the cracks are filled using exemplar-based inpainting method [CP04]. Results on various other images are included in the supplementary material.

8 CONCLUSION

An analysis on varnish layer is described in the paper to understand how it affects the color space of the old paintings and a technique for digital color restoration is proposed. The simulation performed on the number of paintings indicates that satisfactory results can be obtained if we have a clean painting with the similar color distribution as the old painting.

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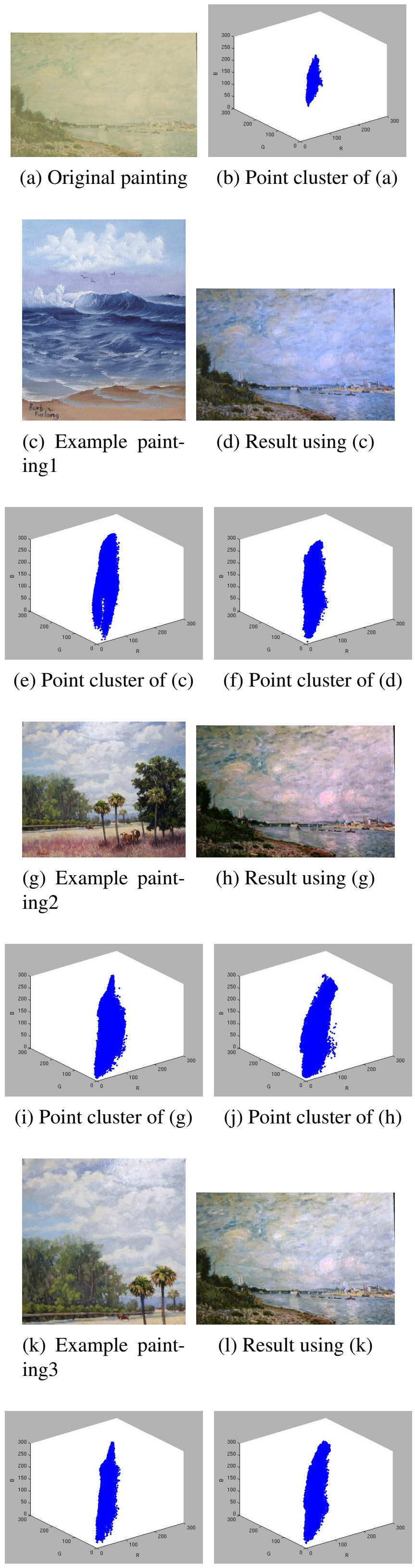


(a) Original painting (b) Point cluster of (a)

(c) Example painting1 (d) Result using (c)

(e) Point cluster of (c) (f) Point cluster of (d)

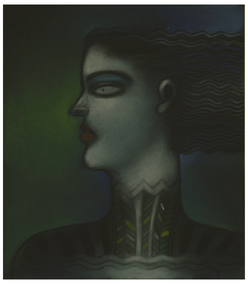
(g) Example painting2 (h) Result using (g)

(i) Point cluster of (g) (j) Point cluster of (h)

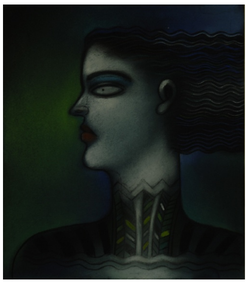
(k) Example painting3 (l) Result using (k)

(m) Point cluster of (k) (n) Point cluster of (l)

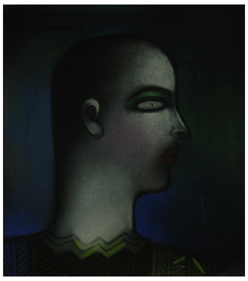
Figure 3: Result to demonstrate the use of different clean paintings for color restoration of an old painting.



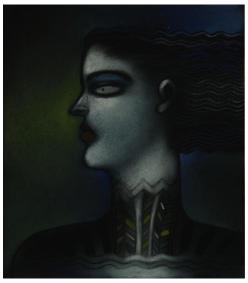
(a) Old Painting



(b) Chemically cleaned painting



(c) Example painting



(d) Restored painting

Figure 4: Result of color restoration

(a) Old painting

(b) Chemically cleaned painting

(c) Example painting

(d) Result

Figure 5: Result of color restoration

(a) Old painting under process of chemical cleaning

(b) cleaned part of the painting

(c) Remaining part is cleaned using digital process

Figure 6: Restoration using cleaned part as sample cleaned painting to complete the cleaning process

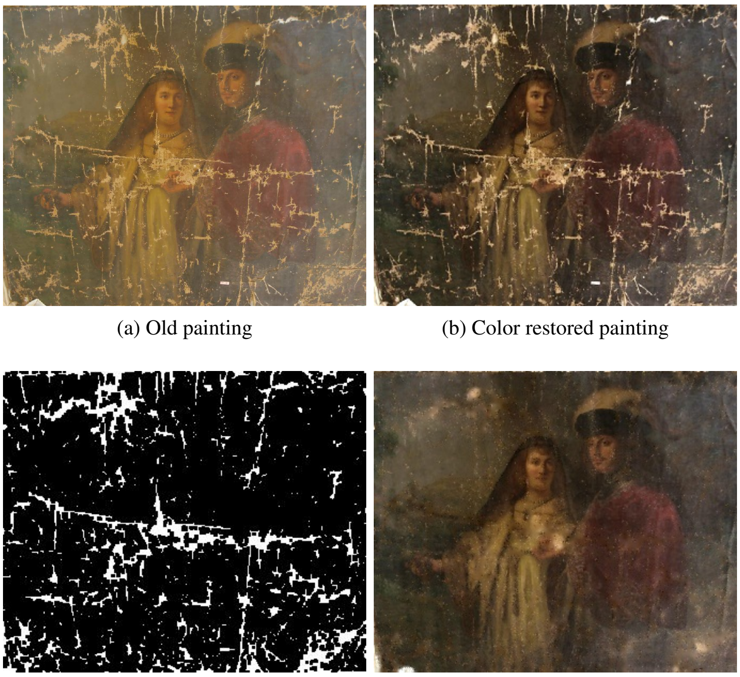
(a) Original painting

(b) Chemically cleaned painting

(c) Example painting

(d) Restored result

Figure 7: Result of color restoration



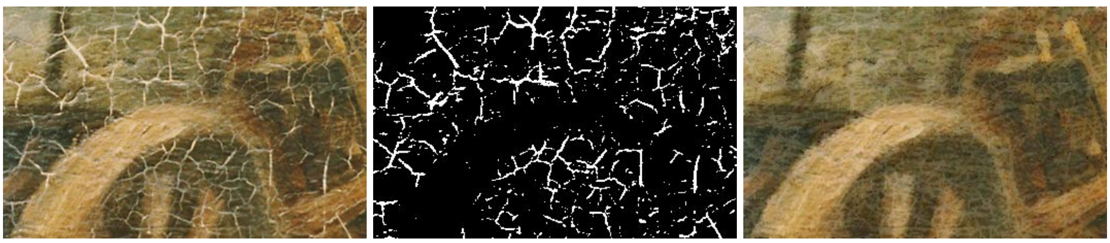
(a) Old painting (b) Color restored painting

(c) Mask (d) After crack filling

Figure 8: Integration of color restoration and crack filling

(a) Original painting (b) Result of crack detection (c) Detected cracks on original painting (d) Result of crack filling

Figure 9: Crack detection and filling



(a) Original image (b) Cracks detected in the image (c) Result after crack filling

Figure 10: Restoration of cracks