Extraction of Artists' Color Features of Art Paintings and its Application to Color Image Correction

***Shoji Tominaga*[1]*, Yoshie Imai*[2]*, Ryoichi Saito*[1]*, and Takahiko Horiuchi*[1]**
[1]*Graduate School of Advanced Integration Science, Chiba University, Chiba, Japan*
[2]*Toshiba Corporation, Kawasaki, Japan*

Abstract

This paper proposes a method to extract artists' color features of art paintings, and correct the color-mismatch images of paintings based on artists' color features. First, we describe a standard image database consisting of famous oil paintings we captured directly, and an algorithm for extracting artists' color features based on the color distribution of the standard image data for each artist. The color distribution is analyzed by PCA and described with an ellipsoid to represent the standard color features for the artist. It is suggested that the color features for the respective artists are similar to the human visual assessment of their paintings. Next, the color correction is based on the coordinate transformation of pixel values in a color-mismatch image so that the color features of the mismatched image are fitted to the artist's color features in the standard image database. We present a correction algorithm using sRGB and CIELAB color spaces. Experiments are performed using samples of color-mismatch images of the famous oil paintings.

Introduction

Color analysis of fine-art paintings is useful in many fields including digital archiving, color reproduction, and image rendering [1]. However, most color images of art paintings which people see are the digital image data, taken by scanning the printed matter in picture collection books or obtained by retrieving museum pictures through Internet. In such a case, we should note that color appearance of the reproduced color images does not match to the color appearance of the original paintings observed under a specific museum lighting environment. The color mismatch occurs in the process including transmission system from image acquisition to image display/printing. The problem of color mismatch cannot be solved as a usual color reproduction problem, because the original observation conditions such as the spectral sensitivities of imaging device and the illuminant spectrum are unknown.

It is thought that an artist painter has peculiar use of color. In fact, there is a report that color features of images from a Web museum were investigated to classify the style of fine-art paintings by individual artists [2]. However we suspect that the colors observed with the images in the Web museum are mismatched colors. In general, individual artists have their own features in painting style, color preference, paints, and materials. Therefore, the information of the individual artists' color features is useful for correcting the mismatched color images. For example, we acquire color images from the original paintings of a particular artist by using a calibrated imaging system to extract his/her color features from the captured images. These color features are available for color correction of the color- mismatch images.

So far we had created a standard image database of individual artists by taking the photographs of the famous paintings in several museums using a calibrated digital camera [3]. The present paper analyzes the color features of each image data set, and proposes a method to correct the color-mismatch images of paintings based on artists' color features.

We first describe the image databases of famous art paintings. Next we present an algorithm for extracting artists' color features. A color histogram is created on a color space to represent the pixel distribution of the standard image data for each artist. Principal component analysis (PCA) is applied to the color histogram to compute eigenvalues and eigenvectors of the dataset. These statistical quantities are regarded as standard color features for the artist. These standard color features are compared with the subjective evaluation of impressions of paintings.

Moreover, we calculate the color distribution of a color mismatch image in the same color space and determine the color features in the same way. Then, the latter color features are transformed to be coincident with the standard color features, so that the color distribution of the color mismatch image is close to the standard features inherent to the artist. As a result, color image correction is performed. We show experimental results to demonstrate the feasibility of the propose method.

Painting Image Databases

Standard Samples of Art Paintings

A large database collecting high resolution digital images (about 4500 × 3500 pixels) of paintings by famous artists was constructed with the photographs taken in the Orsay Museum and the Orangerie Museum in Paris, where photography was permitted. From the dataset, we selected paintings by six artists as shown in Figure 1. The artist names and the numbers of selected artwork paintings are listed as follows:

(1) Paul Cezanne; 7 works
(2) Vincent van Gogh; 7works
(3) Edouard Manet; 7 works
(4) Jean-Francois Millet ; 5 works
(5) Claude Monet; 9works
(6) Pierre-Auguste Renoir; 13 works

Imaging System

We used a calibrated digital RGB camera (Canon EOS 1Ds) with an image resolution of 4992×3883 pixels and a quantization level of 12 bits. The camera sensitivity functions are shown in Figure 2. We found that a good linear relationship exists between the input luminance values to the camera and the output RGB values from the camera.

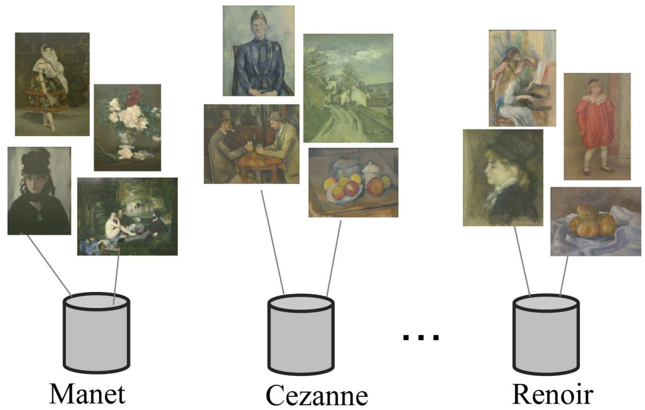


Figure 1. *Standard painting databases.*

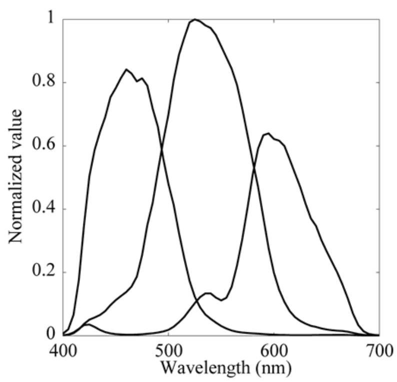


Figure 2. *Spectral sensitivity functions of the camera used in this paper.*

The illumination for each painting is different. The illumination sources observed in the two museums were various light bulbs and daylight through transparent glass windows, so that each painting is basically considered to have different light source. In the image capturing, the light source information was recorded for each painting by using a white reference plate as shown in Figure 3. From this light source observation, we discovered that the correlated color temperature of the light source ranged from 2900K to 6300K.

Image Transformation into Standard Light Source

Since the illumination condition is different among the image dataset, the captured RGB images are transformed into the RGB images under the standard light source of D65. This transformation consists of the following two steps:

1. Determination of correlated color temperature illuminating each painting
2. Transformation to an image viewed under D65 illuminant

First, the color temperature can be determined based on the chromaticity coordinates (x, y) calculated from observations of the white calibration plate.

Figure 3. *Capturing with a white calibration plate.*

Second, the image transformation is done using a color temperature conversion method [4]. Let T and T_o be the color temperatures of the observation illuminant and the illuminant D65, respectively. The camera RGB values captured at the temperature T can be transformed to the color values (R_o, G_o, B_o) at the standard temperature T_o by a simple equation

$$(R_o, G_o, B_o) = (w_R R, w_G G, w_B B), \quad (1)$$

where (w_R, w_G, w_B) are the weighting coefficients. Figure 4 shows the color temperature variation of RGB values for the present camera. Note that the horizontal axis is represented in the reciprocal color temperature, defined by $M = 10^6/T$, and the vertical axis is normalized into 8 bits. Three curves of RGB can be calculated using the black body radiator, the camera-spectral sensitivity functions, and the data set of surface-spectral reflectances. The detailed algorithm is presented in [4]. When T is the color temperature, the weights for conversion to T_o are determined as the ratios $(w_R, w_G, w_B) = (R_o/R_T, G_o/G_T, B_o/B_T)$ of the variation curves in Figure 4.

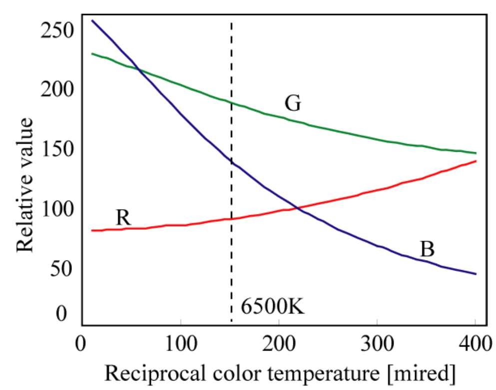


Figure 4. *Color temperature variations of RGB values.*

Color Feature Extraction

PCA of Color Histogram

First, the RGB image data under D65 are transformed into XYZ tristimulus values by multiplication of a 3 × 3 matrix, which is constructed by fitting the spectral sensitivity functions in Figure

2 to CIE 1931 (2deg) color matching functions. We use the sRGB color space and the CIELAB color space as the standard color space for analyzing color features of painting images by different artists. The sRGB color space is commonly used as a standard monitor color space [5]. The sRGB values are calculated from the XYZ tristimulus values. The CIELAB color space is used for approximating a perceptually uniform color space.

The color histogram of all image data acquired for each artist is created in the above coordinate systems of (R, G, B) and (L*, a*, b*). The PCA is applied to the color histogram to compute eigenvalues and eigenvectors of the image dataset for each artist. Note that the size of original paintings is different and also the positions which look at paintings differ. Therefore, in our analysis, the size of original paintings is neglected, and the image size of different paintings is normalized to the nearly same size.

The PCA is known as a method for extracting statistical features of a data set in a linear vector space. Let **c** and $\overline{\mathbf{c}}$ be the 3D column vector of each color value in a color space and the mean vector over all pixels, respectively. The covariance matrix is then described as

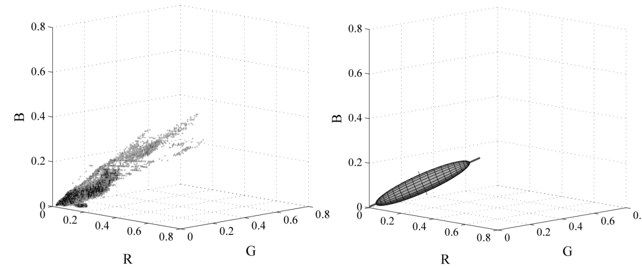
$$\mathbf{A} = \mathbf{E}\left[(\mathbf{c}-\overline{\mathbf{c}})(\mathbf{c}-\overline{\mathbf{c}})^{\mathrm{T}}\right], \qquad (2)$$

where $\mathbf{E}[\bullet]$ denotes the expectation of the random variable, and T denotes matrix transposition. Let $(\lambda_1, \lambda_2, \lambda_3)$, where $(\lambda_1 \geq \lambda_2 \geq \lambda_3)$, and $(\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3)$ be the eigenvalues and the eigenvectors of the matrix **A**, respectively, which satisfy the basic equations

$$\mathbf{A}\mathbf{a}_i = \lambda_i \mathbf{a}_i \quad (i=1, 2, 3). \qquad (3)$$

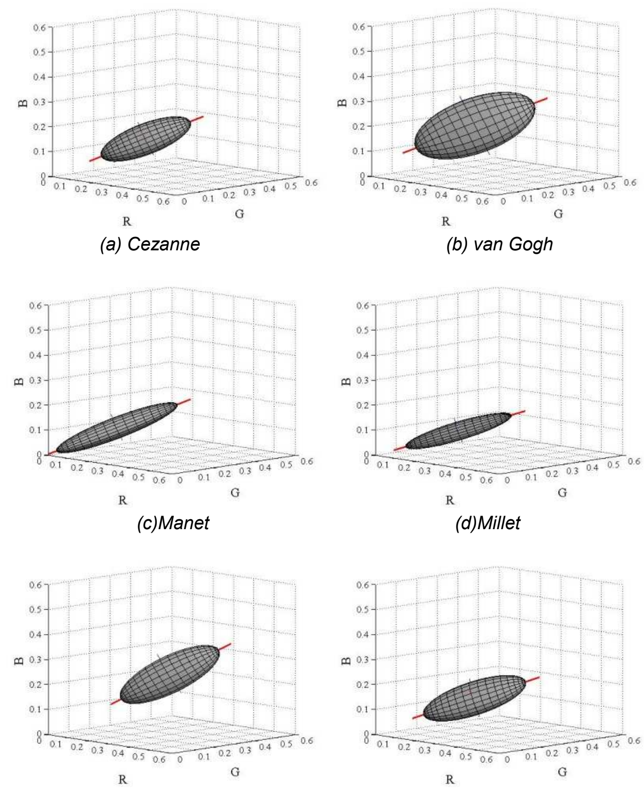
The eigenvectors correspond to the orthogonal directions of the ellipsoid to represent the distribution, and the square roots of the eigenvalues correspond to their lengths. Therefore, $(\mathbf{a}_1, \lambda_1)$ is the first principal component, where $\mathbf{a}_1$ determines the direction of the main axis and λ_1 is the variance along the main axis.

As an example, Figure 5 (a) demonstrates the color distribution of the image set in the sRGB space, which consists of seven paintings by Manet. The PCA is applied to the color distribution. Figure 5 (b) shows the ellipsoid approximation of the color distribution in Figure 5 (a). A comparison between Figures 5 (a) and 5 (b) suggests that the color distribution can be represented effectively by an ellipsoid, and the principal components are regarded as color features.



(a) Color distribution *(b) Ellipsoid*

Figure 5. *Color distribution of image data for Manet.*



(a) Cezanne *(b) van Gogh* *(c)Manet* *(d)Millet* *(e)Monet* *(f) Renoir*

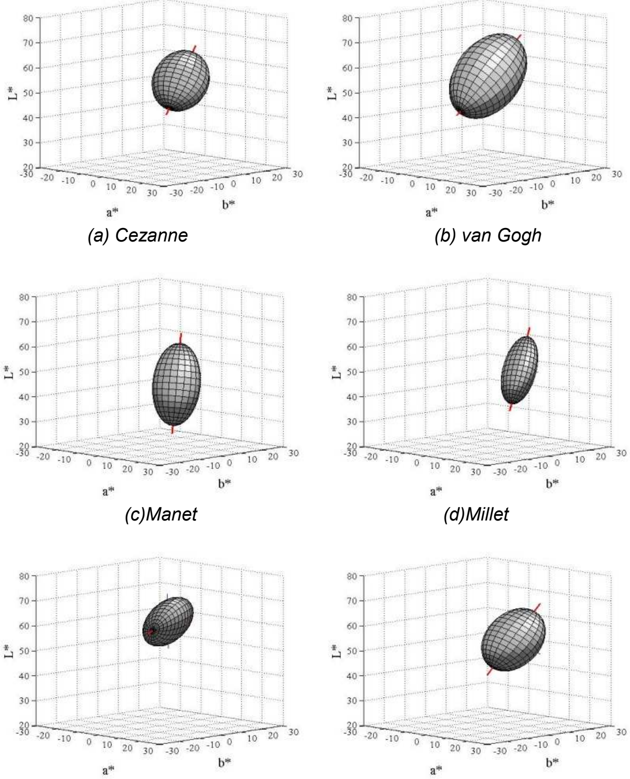
Figure 6. *Ellipsoids for the image datasets of six artists in the sRGB color space under D65.*

Extracted Color Features

Figure 6 shows the ellipsoids obtained from the respective image datasets of the six artists in sRGB color space. Figure 7 shows the corresponding ellipsoids in the CIELAB color space. It should be noted that the positions and the orientations of the ellipsoids differ for every artists. The position is an important feature related to lightness and chromaticity. The size represents the variation of color distribution. For example, the ellipsoid of van Gogh is placed at upper position and large, indicating many colors were used, and the color features were tend to be bright. In contrast, the ellipsoid of Millet is placed at lower position and thin, indicating less color space in his paintings and the color choices are relatively dark. The color features of the six artists determined in this experiment are described as follows:

(1) Cezanne : moderate bright, yellow-greenish
(2) van Gogh : colorful, bright
(3) Manet : dark, less colorful, dull
(4) Millet : dark, less colorful, dull, small color contrast
(5) Monet : bright, color distribution similar to Cezanne
(6) Renoir : colorful, warm

We performed a human visual assessment experiment using all printed color images for all artists in order to validate the artists' color features extracted from the image data. Subjects examined all the reproduced color images. The subjective impression of color features was compared among the image sets for different artists, and the artist's color features were ranked according to the evaluation items. The results of the human visual evaluation for artists were close to the previous results (1)-(6).



(a) Cezanne (b) van Gogh

(c)Manet (d)Millet

(e)Monet (f) Renoir

Figure 7. *Ellipsoids for the image datasets of six artists in the CIELAB color space under D65.*

Application to Color Image Correction

Correction algorithm

The color correction is based on the coordinate transformation of pixel values in a color mismatch image. To do so, the color features of the mismatched image are fitted to the artist's color features in the standard image database. Figure 8 shows the basic principle. The ellipsoid representing mismatch features is transformed to the ellipsoid of standard features by translation, scale, and rotation of the coordinate system. This transformation is applied to all pixel values of the color mismatch image.

First, we calculate the average color vector $\bar{\mathbf{c}}_{\mathrm{M}}$, the eigenvalues $(\lambda_{\mathrm{M1}}, \lambda_{\mathrm{M2}}, \lambda_{\mathrm{M3}})$ and the eivenvectors $(\mathbf{a}_{\mathrm{M1}}, \mathbf{a}_{\mathrm{M2}}, \mathbf{a}_{\mathrm{M3}})$ from a color mismatch image. We define a 3 × 3 eigen matrix $\mathbf{A}_{\mathrm{M}}$ for the color mismatch image as $[\mathbf{a}_{\mathrm{M1}},\ \mathbf{a}_{\mathrm{M2}},\ \mathbf{a}_{\mathrm{M3}}]$. Next, let $\bar{\mathbf{c}}_{\mathrm{S}}$, $(\lambda_{\mathrm{S1}}, \lambda_{\mathrm{S2}}, \lambda_{\mathrm{S3}})$, and $\mathbf{A}_{\mathrm{S}}$ $(=[\mathbf{a}_{\mathrm{S1}}, \mathbf{a}_{\mathrm{S2}}, \mathbf{a}_{\mathrm{S3}}])$ be the mean color vector, the eigenvalues, and the eigen matrix for the standard image dataset, respectively. The color vector $\mathbf{c}$ $(=[R,G,B]^T)$ of the color mismatch image is corrected by a transformation

$$\mathbf{c}' = \bar{\mathbf{c}}_{\mathrm{S}} + \mathbf{A}_{\mathrm{S}}^{-1}\mathbf{\Lambda}\mathbf{A}_{\mathrm{M}}\left(\mathbf{c} - \bar{\mathbf{c}}_{\mathrm{M}}\right), \tag{4}$$

where $\mathbf{\Lambda}$ is a scaling matrix defined by

$$\mathbf{\Lambda} = \begin{bmatrix} \sqrt{\lambda_{\mathrm{S1}}/\lambda_{\mathrm{M1}}} & 0 & 0 \\ 0 & \sqrt{\lambda_{\mathrm{S2}}/\lambda_{\mathrm{M2}}} & 0 \\ 0 & 0 & \sqrt{\lambda_{\mathrm{S3}}/\lambda_{\mathrm{M3}}} \end{bmatrix}. \tag{5}$$

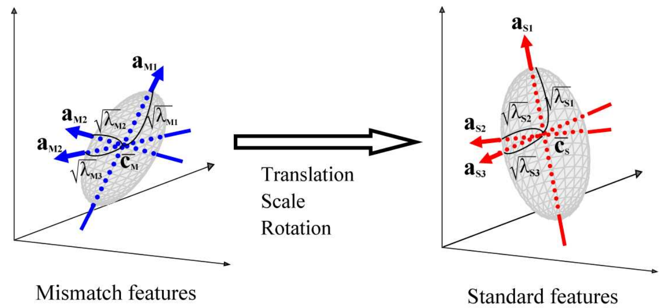


Figure 8. *Basic principle of color correction.*

The above transformation is composed of three basic functions of (1) average matching by translating $\bar{\mathbf{c}}_{\mathrm{M}}$ to $\bar{\mathbf{c}}_{\mathrm{S}}$, (2) axes matching by rotating the principal-components $\mathbf{A}_{\mathrm{M}}$ to $\mathbf{A}_{\mathrm{S}}$, and (3) variance matching by scaling the color distribution by $\mathbf{\Lambda}$. This transformation looks similar to that of scene color transfer [6]. However, the algorithm for scene color transfer did not include the translation step.

The merit of using the CIELAB is that color correction is done in a perceptually uniform color space. Let us compare the artists' ellipsoids in Figure 7 to those in Figure 6. The ellipsoids in the CIELAB look fatter, like rugby balls. In order to suppress the occurrence of false colors by rotation and scale, we emphasize the color transformation to pixels far from the white point (L*, a*, b*) = (100, 0, 0), and emphasize less the transformation to pixels close to the original white point. The additional computation in the CIELAB is described as a weighted average

$$\mathbf{c}'' = w\mathbf{c}' + (1-w)\mathbf{c}_{\mathrm{M}}, \tag{6}$$

where the weighting coefficient w is defined as a distance function from the white point.

The additional computation also can be proposed based on the chroma $C = \left(a^{*2} + b^{*2}\right)^{1/2}$. We emphasize the color transformation to pixels far from the gray axis, and emphasize less the transformation to pixels close to neutral color.

Experimental results

(A) Acquisition of color-mismatch images

Samples of color mismatch images for the famous oil paintings were collected in two ways using a scanner and Internet. One set of painting images was acquired from the scanned pictures in three painting collection books [9]-[11] by using a HP scanner (Scanjet G4050) in the resolution of 200dpi. Another set was acquired from the museum pictures in two websites through Internet [12],[13]. Figure 9 demonstrates three samples of color mismatch images for Monet's "The Fife Player." We notice that the colors of the sample images do not match each other at all. Moreover, Figure 10 demonstrates a sample of color mismatch images for Cezanne's "The Card Players," which was acquired from the book [12].

(a) Picture book S (b) Picture book N (c) Internet 1

Figure 9. *Samples of color mismatch images for Manet's "The Fife Player."*

Figure 10*. Sample of color mismatch image for Cezanne's "The Card Players."*

(B) Color correction results

The color correction algorithm was applied to the three images in Figure 9. The ellipsoids of Manet in Figure 6 (c) based on the seven selected color images in the database were used as the color features in the sRGB color spaces under D65. To evaluate if the proposed method is able to recover the exact color images, the color features were recomputed from the set of Manet's paintings, excluding the Fife Player.

The original painting of The Fife Player was photographed in the Orsay Museum by our imaging system. The correlated color temperature of illuminant was determined as 3151K by using the white reference plate. The camera image was transformed to the standard image under D65 Illuminant by using the color image transformation procedure. Figure 11 shows the camera image and the standard image. Figure 12 shows the correction results for the image in the CIELAB color space by using the color temperature estimation procedure under D65 Illuminant and Eq.(6).

For numerical evaluation, we calculated the color difference ΔE^*_{ab} between the original image in Figure 9 and the standard color image in Figure 11 (b), and also between the corrected color images in Figure 12 and the standard color image. All color differences are summarized in Table 1, where the original algorithm in Eq.(4) for sRGB was used in the sRGB color space. It is found that all color-mismatch images improved in the sense of numerical color difference.

(a) Camera image (b) Standard image (D65)

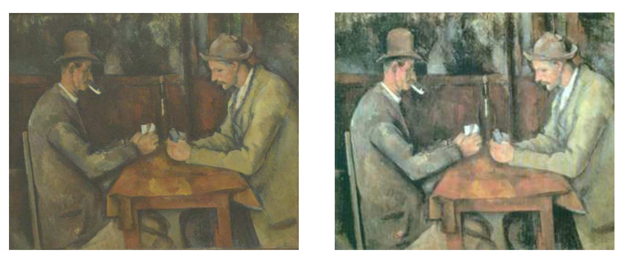
Figure 11. *Camera image and standard image of the Fife Player by Manet.*

(a) Picture book S (b) Picture book N (c) Internet 1

Figure 12. *Color correction results in the CIELAB color space.*

Table 1 Color differences in correction for images in Figure 12.

Sample	Original	Color correction	
		sRGB	CIELAB
(a)	42.5	13.6	13.5
(b)	14.9	14.3	11.3
(c)	14.1	12.1	12.1



(a) Standard image (D65) *(b) Corrected image with the chroma adjustment in the CIELAB color space.*

Figure 13. *Color correction results for Cezanne's "The Card Players."*

Figure 13 demonstrates the correction results for Monet's "The Fife Player." The original painting also was photographed in the Orsay Museum by our imaging system. Figure 13 (a) shows the target standard image under D65 Illuminant, and Figure 13 (b) shows the corrected image by using Eq.(6) with the chroma adjustment in the CIELAB color space. We should note the correction accuracy in comparison with Figure 10.

Conclusion

The present paper has proposed a method to extract artists' color features of art paintings, and correct the color-mismatch images of paintings based on artists' color features.

First, we described a standard image database consisting of famous oil paintings we captured directly, and an algorithm for extracting artists' color features based on the color distribution of the standard image data for each artist. The color distribution was analyzed by PCA and described with an ellipsoid to represent the standard color features for the artist. It was suggested that the color features for the respective artists were similar to the human visual assessment of their paintings.

Next, the color correction was based on the coordinate transformation of pixel values in a color-mismatch image so that the color features of the mismatched image were fitted to the artist's color features in the standard image database. We presented the correction algorithm using the sRGB color space. Experiments were performed using samples of color-mismatch images of the famous oil paintings, which were collected from painting picture books and Internet. The feasibility was confirmed on the evidences of the correction results.

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Author Biography

Shoji Tominaga received the Ph.D. degree from Osaka University, Japan in 1975. He had been with Osaka Electro-Communication University from 1976 to 2006. He was a professor at Chiba University from 2006 to 2013. During 1987-1988 he was a Visiting Scholar at Stanford University. He is now a specially appointed researcher at Graduate School of Advanced Integration Science, Chiba University. He is a Life Fellow of IEEE, and a Fellow of IEICE, IS&T, and SPIE.