Color Image Enhancement by Highlight-Preserving Vector Transformation and Nonlinear Mapping

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Abstract

In this paper, a new light-value approaching method to enhance a color image by excluding the effect of incident illumination is proposed. The method uses the highlight-preserving vector transformation, in which an estimated color of illumination is transformed to the white color of natural daylight while preserving the highlight. In the method, initial transformation matrix using simple vector rotation is corrected by regression, and the corrected transformation matrix is applied to input color. Then the transformed red, green, and blue values of each pixel are nonlinearly mapped to the 8 bit values to be displayed on natural color output device. The proposed method can produce the enhanced color image fast and efficiently without any space conversion or noticeable distortion.

1. Introduction

The challenge to enhance color images has intensified due to the rapid development of color video media and color desktop publishing. The ability to both improve the natural color of images by excluding the effect of incident illumination and yet preserve the particular detailed information of the image is extremely important.[1-7]

The intrinsic chromatic properties of objects in the image are given by surface reflectance functions, which specify the proportion of incident illumination reflected by a surface as a function of wavelength. The recovery of surface reflectance functions from light that reaches our eyes is a complex task since the reflected light is a composite signal: it depends on both surface reflectance and the spectral power distribution of the illumination. However, human vision has color constancy which, in general terms, uses a process whereby the perceived color of the object remains invariant under changes of illumination color.[1-4] The mechanisms that provide color constancy must decompose this signal and discount the spectral properties of the illumination to establish the colors of objects in terms of their surface reflectance functions.

Most of the research that has been done to enhance color image using the color constancy has been theoretical, involving the study of mathematical constraints under which color constancy might be possible and the analyses of the quantitative properties of previously proposed mechanisms. Recently, some realizable constancy algorithms were developed which fall into two categories, so called wavelength approaching and light-value (gray level) approaching methods. In the wavelength methods[1-5], all the computation is carried out in the wavelength domain, therefore, they are not applicable in current image processing systems in which a digitized light value is used. In light-value approaching methods[6,12], the hue is preserved and the intensity and saturation are enhanced. However, in the methods, color space conversion is required, e.g. RGB to HIS(Hue, Saturation, and Intensity), RGB to HSV(Hue, Saturation, and Value), or other conversions. Thus, these conversions tend to yield a color distortion due to the gamut difference of each space.

In this paper, a new light-value approaching method is proposed which uses a digitized RGB value of a color image under various illuminations. In this method, the pixel of a color image is represented as a 3-dimensional vector with red, green, and blue light-value components. The natural illumination appears white and can be described as a unit vector in the RGB color space. The unknown color of illumination used in the image capture is estimated as mean vector of which the components are spatial means of red, green, and blue images. Consequently, the proposed transformation can be defined as vector rotation, in which the estimated color of the unknown illumination is transformed to the white of the natural illumination. The rotation angle and the equivalent axis are computed as the difference angle and the orthonormal vector between the white and the estimated illumination color, respectively. Next, a 3×3 homogeneous transformation matrix with about the equivalent axis is made and the input color of each pixel is transformed into a new R’G’B’ color space using the matrix. However, if there are highlights in input image, we may see that the region is distorted by the proposed method. This effect, we think, is due to the over-transformation of
highlight. Therefore, in order to reduce this effect, an adjusted transformation function is needed. In this paper, the initial transformation matrix is corrected by regression based on finding a mapping, which maps highlight to highlight without distortion. Then, the correctly transformed red, green, and blue color values of each pixel in the new space are non-linearly mapped to integer values between 0 and 255 for 24-bit natural color display. The proposed method can restore the natural color in images by excluding the effect of incident illumination and then enhance the image quality.

In the experiment, the proposed method is simulated on synthetic color patch images and other natural color images, and compared with equalization method. In that, it is shown that the proposed method can effectively decrease the effect of illumination in any color image.

2. The Proposed Color Image Enhancement Method

Color images captured by a color camera or other devices consist of red, green, and blue monochrome images based on three principle colors of light. Each pixel of the monochrome images is digitally quantized with an 8-bit value and the color image display system can describe nearly 16 million colors giving a total of 24 bits. But the captured image has different characteristics depending on the illumination used. If the illumination is tungsten light, the captured image is reddish, alternatively, if the illumination is fluorescent light or skylight, the captured image is very bluish. This is caused by the fact that the color image capture system is merely passively recording the image. However, human vision automatically and instantaneously performs internal computations based on color constancy and the computations produce images of high quality.

2.1. Color Constancy Theory

Color constancy refers to the perceptual stability of the appearance of surface color under conditions of changing unknown illumination. This constancy can be posed as a computational problem: how can the visual system recover the spectral properties of the surfaces that it sees and maintain the physical properties that do not depend on the variations of illumination from photo receptor signals? One approach to the problem relies on finite-dimensional linear models of surface reflectance functions and light source spectral functions. The linear models are used to construct a deterministic model of the change in the reflected lights caused by changing illumination. The image formation process is then inverted to recover the spectral descriptors of lights and surfaces. Schemes of this sort include two-stage linear recovery schemes, a more general one stage linear recovery scheme, and various nonlinear recovery schemes. Variations on this approach used additional information such as highlights or inter-reflections to help recover spectral descriptions. However, most previous research to recover surface spectral has been theoretical, involving studies of the mathematical constraints under which the color constancy might be possible and the analyses of the quantitative properties of previously proposed mechanisms. In the previous algorithms, all the computation is carried out in the wavelength domain, which is not appropriate in current image processing systems that use digitized light value (gray level).

2.2. Finding an Unknown Illuminant

In the color image enhancement method based on the color constancy, it is important to estimate the unknown illuminant used in the image capture. Previously, several different methods were proposed to estimate the chromaticity of the illuminant in the image. There are many estimation methods, for example, a method which uses the brightest surface in the early retinex scheme of Land and McCann, a method which uses information from the highlights (specular reflectance) of an image, and a method which uses the space-averaged chromaticity in image. In the first method, which uses the brightest surface, the color constancy fails if there is no bright white region in a image. The second method is not appropriate for flat, matte surfaces such as papers in Mondrian. However, in the case of the last method, there are no limitations such as in the previous methods. There can be images in which the chromaticity of the average light departs significantly from that of the illuminant, however, we expect that the space-averaged light from most natural images will bear a chromaticity that closely approximates that of the illuminant. Buchsbaum first formulated the gray world assumption which holds that the space-averaged reflected light bears the chromaticity of the illuminant, and used this assumption to estimate the spectral properties of an unknown light source from the space-averaged reflected light. This estimate was then used to recover the reflectance properties of individual surfaces.

In this paper, the computation method of the space average is a little different from the previous one that simply computes the mean of each monochrome image. The space average is computed as a spatial mean of the result of the vector median in a 3×3 local block of image, as follows.
\[
R_{av} = \frac{1}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} R\{vmed(\vec{C}_{i+k,j+l})\}
\]
\[
G_{av} = \frac{1}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} G\{vmed(\vec{C}_{i+k,j+l})\}
\]
\[
B_{av} = \frac{1}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} B\{vmed(\vec{C}_{i+k,j+l})\}
\]
(1)

where the space average chromaticity can be described as a color vector \( \vec{C}_{av} = [R_{av}, G_{av}, B_{av}]^T \). \( N \) and \( M \) are the column and row size of the image, \( R[] \), \( G[] \), and \( B[] \) are the red, green, and blue components of the vector median, \((i,j)\) is the pixel position, and \(-1 ≤ k, l ≤ 1\), respectively. The vector median is a color vector which has a minimal angle difference in the 3×3 local block. The angle difference and the vector median are computed by

\[
A(\vec{C}_{p}) = \frac{1}{n} \sum_{m=0}^{n-1} \cos^{-1}\left(\frac{\vec{C}_{p} \cdot \vec{C}_{m}}{|\vec{C}_{p}| |\vec{C}_{m}|}\right), \quad 0 ≤ p ≤ n - 1
\]
\[
vmed(\vec{C}) = \vec{C}_{p} \quad \text{if} \quad \min A(\vec{C}_{p})
\]
(2)

where \( n \) is 9 as the number of samples in the 3×3 local block and \( \cdot \) means the dot-product of the vector. The space average computation using the vector median can reduce the noise, but the original color of input image is not changed.

**2.3. Fundamental Vector Transformation**

As shown above, 3-dimensional vectors of red, green, and blue components describe color image. Therefore, if a high mutually correlated monochrome image is individually processed by each different enhancement method, the separated enhancement processes cause a severe color distortion due to a change in hue. In this paper, the proposed enhancement process is a fundamental vector transformation method, in which the 3-dimensional color vector of a pixel is processed at the same time. The proposed transformation is defined as a vector rotation\(^8\) of the previously estimated illuminant to the reference white of natural illumination like daylight, CIE D65 or C. The reference white can be described by a unit vector in RGB coordinate, \( \vec{C}_w = [255 \quad 255 \quad 255]^T = [1 \quad 1 \quad 1]^T \).

Then, the estimated color of the unknown illumination is rotated to the white of the natural illumination. The rotation angle and the equivalent axis are computed as the difference angle and the orthonormal vector between the white and the estimated illumination color, respectively. The rotation angle is computed by

\[
\theta = \cos^{-1}\left(\frac{\vec{C}_{w} \cdot \vec{C}_e}{|\vec{C}_w| |\vec{C}_e|}\right) = \cos^{-1}\left(\frac{(R_{aw} + G_{aw} + B_{aw})}{\sqrt{3(R_{aw}^2 + G_{aw}^2 + B_{aw}^2)}}\right)
\]
(4)

And the equivalent axis is computed by the cross-product of the two vectors, as follows.

\[
\vec{C}_e = \vec{C}_{aw} \times \vec{C}_w
\]
(5)

where \( \vec{C}_e \) is the equivalent axis and \( \times \) means the cross-product. The unit vector of the axis is described by

\[
\vec{U}_e = \frac{\vec{C}_e}{|\vec{C}_e|} = \left[U_{er} \quad U_{eg} \quad U_{eb}\right]^T
\]
(6)

Then, a 3×3 homogeneous transformation matrix about the equivalent axis is made by

\[
F = \begin{bmatrix}
f_{11} & f_{12} & f_{13} \\
f_{21} & f_{22} & f_{23} \\
f_{31} & f_{32} & f_{33}
\end{bmatrix}
\]
(7)

\[
f_{11} = U_{er} (1 - \cos \theta) - U_{eg} \sin \theta
\]
\[
f_{12} = U_{er} \sin \theta + U_{eg} (1 - \cos \theta)
\]
\[
f_{13} = U_{eb} (1 - \cos \theta)
\]
\[
f_{21} = U_{eg} (1 - \cos \theta) - U_{er} \sin \theta
\]
\[
f_{22} = U_{eg} \sin \theta + U_{er} (1 - \cos \theta)
\]
\[
f_{23} = U_{eb} (1 - \cos \theta)
\]
\[
f_{31} = U_{eb} \sin \theta
\]
\[
f_{32} = U_{eb} \sin \theta
\]
\[
f_{33} = U_{eb} \sin \theta
\]
(8)

The color vector of the pixel \((i,j)\) in the image is transformed to a new R’G’B’ coordinate using the transformation matrix, as follows.

\[
\vec{C}'_{ij} = F \cdot \vec{C}_{ij}
\]
(9)

The color vector \( \vec{C}_e = [R_{eg} \quad G_{eg} \quad B_{eg}]^T \) in the new coordinate can construct the image in which the effect of various illuminations is removed efficiently, while the important characteristics of the original image such as the edge is not changed at all.

**2.4. Transformation Matrix Correction by Regression**

If there are highlights in input image, we may see the result image has distortion due to over-transformation of highlight. Therefore, the initial transformation matrix needs to be adjusted. In the proposed method, the initial matrix is corrected by regression, in which the highlight is preserved without distortion\(^9\).

The highlight can be defined as bright white that has saturation close to zero and hue of original object. In the
proposed method, highlights in input image were detected as colors that have lightness larger than 220 and the mutual differences, among red, green, and blue light values, less than 20. The detected highlights are described as vector, \( \vec{C} \).

The regression is a method for mapping RGBs to R'G'B' s such that the sum of least-squares residuals is minimized subject to the constraint that highlight is mapped without error. The regression used in this paper is described as follows.

\[
E = \sum_{i=1}^{K} \| \vec{C}'_i - F^* \vec{C}_i \|^2 + \lambda \sum_{p=1}^{K} \| \vec{C}'_p - F^* \vec{C}_p \|^2
\]

where \( K \) is the number of the detected highlight colors and multiplier \( \lambda \) is set to 1 and \( \vec{C}'_i = F \vec{C}_i \). Then, taking partial derivatives with respect to the elements of \( F^* \), we arrive at the Euler equations and a solution is

\[
F^* = ( R^T R )^{-1} R^T H
\]

where \( NM \times 3 \) matrix, \( R^T \) consists of transposed vectors of \( \vec{C}'_i \) and \( \vec{C}'_p \), and \( NM \times 3 \) matrix, \( H \) consists of transposed vectors of \( \vec{C}_i \) and \( \vec{C}_p \). Then, we use \( F^* \) instead of \( F \) in eq.(9).

### 2.5. Nonlinear Mapping

The proposed nonlinear mapping can be defined as a re-quantization to 8 bit integer values in each monochrome image. The transformed values are in float variable domain. Therefore, the re-quantization of the transformed values to 8 bits is necessary because the pixel values of each monochrome image are stored as 8 bit integer values and can be displayed on natural color display devices. The proposed re-quantization uses the \( \mu \)-law quantization method usually used in a companding system.\(^{[10]}\) The \( \mu \)-law is expressed as

\[
y = \text{int} \left[ y_{\text{max}} \frac{\log \left( 1 + \mu \left| x / y_{\text{max}} \right| \right)}{\log \left( 1 + \mu \right)} \right]
\]

where \( \mu \) is a positive constant, \( x \) and \( y \) represent input and output values, \( y_{\text{max}} \) and \( y_{\text{max}}(=255) \) are the maximum positive excursions of input and output values, and the \( \text{int}[ \cdot ] \) function converts the inside computed float value to an 8-bit integer value, respectively. Using this method, the hue of a pixel color of an image and the particular details are almost preserved and unchanged, and, at the same time, the whole quality of the image is improved.

### 3. Experiment

In the experiment, we synthesized 256×256 color patch images that were composed of samples from the Munsell color book in order to test the proposed vector transformation method. In the image, 8 colors were made and properly arranged with a graphic tool. In Fig. 1, (a) is the synthesized original image, (b) is under illumination D65, and (c) is under illumination A. The proposed algorithm is applied to both (b) and (c). Fig. 1(d) and (e) show the results of the proposed method, where both the result images are similar to the original. The errors between the original and the captured, as well as between the original and the results, are computed as a mean of the Euclidean distance in the L*\(a*\)\(b*\) color space. Table 1 shows the comparisons of the space average and the L*\(a*\)\(b*\) error (\( \forall e_{ab} \)) between the original and the other images.

We compared the proposed method with the equalization method, as shown in Fig.2. Fig. 2 (a) and (b) are original synthetic images under illuminants A and D65, (c) and (d) the equalized results, and (e) and (f) the results by the proposed initial vector transformation and nonlinear mapping. In that, the proposed method has better performance than the equalization method, so that the illuminant effect is efficiently removed. Fig. 3 shows the natural and the result images, in which (a) is original, (b) the equalized image, (c) the result by the proposed initial vector transformation, and (d) the result by the proposed corrected vector transformation using regression. We can see that in Fig.3 (b), surrounding illuminants are not removed, but in Fig.3 (c) and (d), the illuminant effect is efficiently removed. Also comparing the Fig.3 (c) and (d), the highlight is not preserved in (c) but preserved in (d).

As shown above, the proposed method can decrease the effect of illumination. At the same time, the quality of the image is enhanced while preserving the hue and particular detailed information of input image.

### 4. Conclusion

The proposed vector transformation method can restore the natural color in various images by excluding the effect of incident illumination and nonlinear mapping can enhance the quality of the image. This method is appropriate for current image systems which use digitized light values. However, if the estimation of unknown illumination using the spatial average fails, the proposed method cannot function. So, we will continue to find the optimal method for estimation of the unknown illumination.
5. References


![Figure 1](image1.png)

**Figure 1.** Synthetic image; (a) original image, (b) captured under D65, (c) captured under A, (d) the result of (b), and (e) the result of (c).

![Figure 2](image2.png)

**Figure 2.** The comparison of equalization and the proposed method; (a) input images which includes white and black in illuminants A and D65, (b) input images which does not include white and black in illuminants A and D65, (c) the result images of equalization method in each input images of (a), (d) the result images of equalization method in each input images of (b), (e) the result images of the proposed method in each input images of (a), and (f) the result images of the proposed method in each input images of (b), respectively.

<table>
<thead>
<tr>
<th>Image</th>
<th>Space average</th>
<th>Between</th>
<th>L<em>a</em>b* Error</th>
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<tr>
<td>(a)</td>
<td>[91.92, 93.48, 92.48]</td>
<td>(a) &amp; (b)</td>
<td>3.7</td>
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<tr>
<td>(b)</td>
<td>[91.33, 94.37, 87.14]</td>
<td>(a) &amp; (c)</td>
<td>26.96</td>
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<td>(a) &amp; (d)</td>
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<td>(e)</td>
<td>[86.49, 86.47, 86.30]</td>
<td>(a) &amp; (f)</td>
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**Table 1.** Comparisons of space average and L*a*b* error between the original and the other images in Fig. 1.

![Figure 3](image3.png)

**Figure 3.** A natural image; (a) original image, (b) histogram equalized image, (c) the result by initial transformation matrix, and (d) the result by corrected transformation matrix using regression, respectively.