Color Image Enhancement by Fundamental 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 fundamental vector transformation in which an estimated color of illumination is rotated to the white color of natural daylight. Then the transformed red, green, and blue values of each pixel are nonlinearly mapped into the 8 bit values to enhance intensity and saturation in the dark portion of the image. The proposed algorithm can produce the enhanced color image fast and efficiently without any space conversion or noticeable distortion.

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.[1-10]

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 a 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 algorithms[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 algorithms[6], the hue is preserved and the intensity and saturation are low-pass filtered, equalized, and contrast-enhanced. However, in these methods, color space conversion is required, e.g. RGB to HSI(Hue, Saturation, and Intensity), RGB to HSV(Hue, Saturation, and Value), and other conversions. Thus, these conversions tend to yield a color distortion due to the gamut difference of each space.

In this paper, some of the previous color constancy algorithms were analyzed and 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 a mean color vector of which the components are spatial means of red, green, and blue images. Consequently, the proposed vector transformation can be defined as fundamental vector rotation, in which the estimated color vector of the unknown illumination is rotated to the white color 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 4×4 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. The transformed red, green, and blue color values of each pixel in the new space are non-linearly mapped into an integer value between 0 and 255 for 24-bit natural color display on the monitor. The proposed method can first restore the natural color in images by excluding the effect of incident illumination and then enhance the image intensity and saturation by correcting the dark portion.

Color Image Enhancement by Fundamental Vector Transformation

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. In this paper, the previous color constancy algorithms are analyzed and a new automatic color image enhancement method based on constancy is proposed.

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.[1-5] 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 which use digitized light value(gray level).

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[3-5]. 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[1], a method which uses information from the highlights(specular reflectance) of an image[4], and a method which uses the space-averaged chromaticity in image[3,6]. 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.[3]

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[7] in a 3×3 local block of image, as follows.

$$
\begin{aligned}
R_{ave} &= \frac{1}{(N-1)(M-1)} \sum_{i=1}^{N-1} \sum_{j=1}^{M-1} R\{vmed(\vec{C}_{i+k,j+l})\} \\
G_{ave} &= \frac{1}{(N-1)(M-1)} \sum_{i=1}^{N-1} \sum_{j=1}^{M-1} G\{vmed(\vec{C}_{i+k,j+l})\} \\
B_{ave} &= \frac{1}{(N-1)(M-1)} \sum_{i=1}^{N-1} \sum_{j=1}^{M-1} B\{vmed(\vec{C}_{i+k,j+l})\}
\end{aligned}
\tag{1}
$$

where the space average chromaticity can be described as a color vector by $\vec{C}_{ave} = [R_{ave}\ G_{ave}\ B_{av}]^T$, 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 $-1 \le k, l \le 1$, 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

$$A(\vec{C}_p) = \frac{1}{n}\sum_{m=0}^{n-1}\cos^{-1}\left(\frac{\vec{C}_p \bullet \vec{C}_m}{|\vec{C}_p||\vec{C}_m|}\right), \quad 0 \le p \le n-1 \quad (2)$$

$$vmed\ (\vec{C}) = \vec{C}_p \quad \text{if} \quad \min\ A(\vec{C}_p) \quad (3)$$

where n is 9 as the number of samples in the 3×3 local block and • means the dot-product of the vector.

The space average computation using the vector median can reduce the noise and the effect of a highlight component.

Fundamental Vector Transformation

As shown above, the color image is described by a 3-dimensional color vector of red, green, and blue components. 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 a RGB coordinate, as follows.

$$\vec{C}_w = [255 \quad 255 \quad 255] = [1 \quad 1 \quad 1]^T \quad (4)$$

Then, the estimated color vector of the unknown illumination is rotated to the white color 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

$$\theta = \cos^{-1}\left(\frac{\vec{C}_w \bullet \vec{C}_{ave}}{|\vec{C}_w||\vec{C}_{ave}|}\right) = \cos^{-1}\left(\frac{(R_{ave} + G_{ave} + B_{ave})}{\sqrt{3}\sqrt{(R_{ave}^2 + G_{ave}^2 + B_{ave}^2)}}\right) \quad (5)$$

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

$$\vec{C}_e = \vec{C}_{ave} \times \vec{C}_w \quad (6)$$

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

$$\vec{U}_e = \frac{\vec{C}_e}{|\vec{C}_e|} = [U_{eR} \quad U_{eG} \quad U_{eB}]^T \quad (7)$$

Then, a 4×4 homogeneous transformation matrix about the equivalent axis is made by

$$R(\theta, \vec{U}_e) = \begin{bmatrix} r_{11} & r_{12} & r_{13} & 0 \\ r_{21} & r_{22} & r_{23} & 0 \\ r_{31} & r_{32} & r_{33} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (8)$$

$$\begin{aligned}
r_{11} &= U_{eR}^2(1-\cos\theta) + \cos\theta \\
r_{12} &= U_{eR}U_{eG}(1-\cos\theta) - U_{eB}\sin\theta \\
r_{13} &= U_{eR}U_{eG}(1-\cos\theta) + U_{eG}\sin\theta \\
r_{21} &= U_{eR}U_{eG}(1-\cos\theta) + U_{eB}\sin\theta \\
r_{22} &= U_{eG}^2(1-\cos\theta) + \cos\theta \\
r_{23} &= U_{eG}U_{eB}(1-\cos\theta) - U_{eR}\sin\theta \\
r_{31} &= U_{eR}U_{eB}(1-\cos\theta) - U_{eG}\sin\theta \\
r_{32} &= U_{eG}U_{eB}(1-\cos\theta) + U_{eR}\sin\theta \\
r_{33} &= U_{eB}^2(1-\cos\theta) + \cos\theta
\end{aligned} \quad (9)$$

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.

$$\begin{bmatrix} R'_{i,j} \\ G'_{i,j} \\ B'_{i,j} \\ 1 \end{bmatrix} = R(\theta, \vec{U}_e) \begin{bmatrix} R_{i,j} \\ G_{i,j} \\ B_{i,j} \\ 1 \end{bmatrix} \quad (10)$$

The color vector $\vec{C}' = [R_{ij}' G_{ij}' B_{ij}']^T$ 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. However, the intensity or saturation of the image, and the colors in the dark local region are not enhanced by using vector rotation. In this paper, a nonlinear re-mapping method is used to enhance the intensity and saturation with no distinguishable hue change in the dark region.

Nonlinear Mapping

The proposed nonlinear mapping method can be defined as a re-quantization to 8 bit integer values in each monochrome image. The vector transformed values are in a float variables 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. The proposed re-quantization uses the μ-law quantization method usually used in a companding system.[9] The μ-law is expressed as

$$y = \text{int}[y_{\max}\frac{\log_e(1+\mu|x|/x_{\max})}{\log_e(1+\mu)}] \quad (11)$$

where μ is a positive constant, x and y represent input and output values, x_{max} and y_{max}(=255) are the maximum positive excursions of input and output values, and the int[ ] 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. But, at the same time, the intensity and saturation of the dark portion in the image is enhanced. Consequently, the whole quality of the image is improved.

Experiment

In the experiment, we synthesized 256×256 color patch images which 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. The result shows that the proposed algorithm can decrease the error significantly. Table 1 shows the comparisons of the space average and the L*a*b* error(∇E_{ab}) between the original and the other images from Fig. 1. And it is certified from a CIE xy chromaticity diagram as in Fig. 2. Fig. 3 shows the original natural images and the results after applying the proposed vector transformation and nonlinear mapping method. The saturation and intensity in the dark portion of the image are enhanced while preserving the hue and particular detailed information of the input image.

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 intensity and saturation in the dark portion 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.

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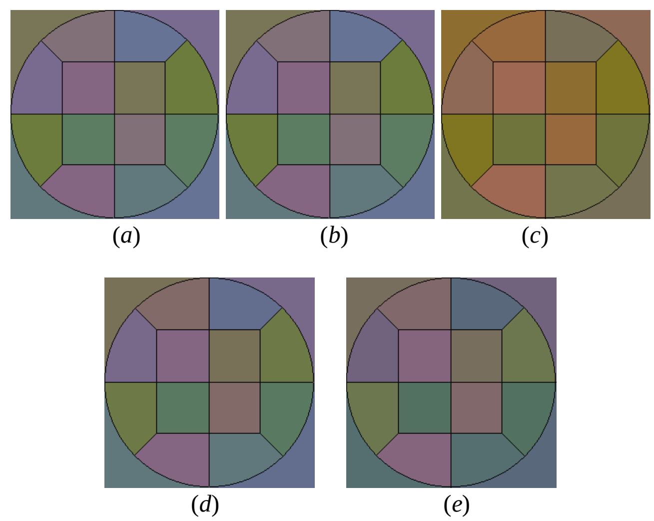

Fig. 1. Synthesized image; (a) original image, (b) captured under D65, (c) captured under A, (d) the result of (b), and (e) the result of (c).

Table 1. Comparisons of space average and L*a*b* error between the original and the other images in Fig. 1.

Image	Space average	Between	L*a*b* Error
(a)	$[91.92, 93.48, 92.48]^T$	(a) & (b)	3.7
(b)	$[91.33, 94.37, 87.14]^T$	(a) & (c)	26.96
(c)	$[111.01, 88.89, 49.12]^T$	(a) & (d)	2.65
(d)	$[90.73, 90.48, 90.42]^T$	(a) & (e)	6.95
(e)	$[86.49, 86.47, 86.30]^T$		

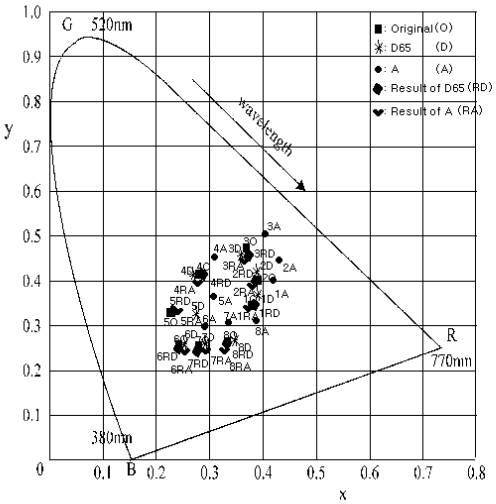

Fig. 2. CIE xy chromaticity diagram of 8 colors in Fig. 1. (■: color in original, ∗: color in D65, •: color in A, ♦: color in the result of D65, and ♥: color in the result of A.)

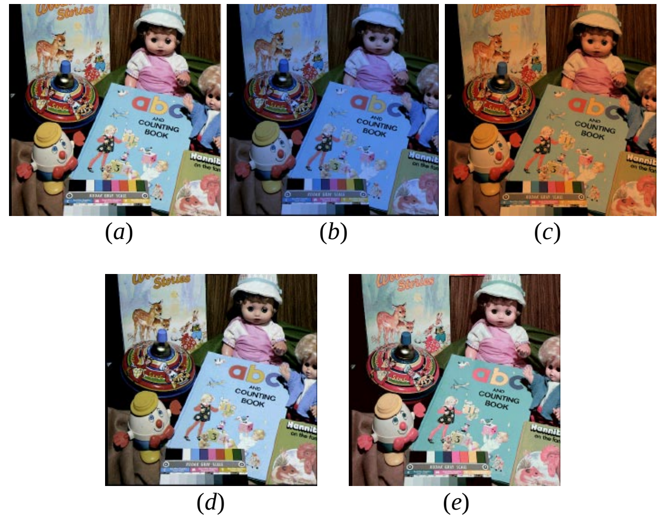

Fig. 3. Toy image; (a) original under sunlight, (b) captured under blue-sunlight, (c) captured under tungsten light, (d) the result of (b), and (e) the result of (c).