Dichromatic Based Photographic Modification

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Abstract

We propose a technique to modify colors in photographic images predicting the color appearance of objects in an image under different illuminations. Using the dichromatic surface reflectance model[13], we estimate the illumination spectrum and the spectrum of the diffuse surface reflectance via the color histogram and subspace analyses. With this estimated spectral information, and the spectrum of a newly specified illumination, we construct two color correction operators, one for the specular reflection color component and the other for the diffuse reflection color component, to modify color values in the images. We demonstrate this new method with a skin tone modification example using a human face subject.

1. Introduction

With the increase use of digital image devices such as digital cameras, the research in the digital photography receives more and more attention. Many digital photography applications need to modify colors in images to predict the appearance of objects under different lighting conditions. It is not easy to achieve this while keeping the lighting consistent, since colors obtained from a digital imaging device are formed in a series of complex processes. It involves the physical processes of light being emitted from light sources, transmitted through media, reflected and transported between surfaces, and finally being collected on the color sensors of an image capture device[11]. In General, an accurate color correction operation for this purpose requires partial or full recovery of the spatial and spectral distributions of the illumination, the three dimensional geometry and reflectance properties of object surfaces. With only two-dimensional information at three-color channels, simplifications have to be introduced to make this problem solvable under some special circumstances. In most situations, the 3D geometry of objects and the spatial configuration of the light sources, the objects and the camera are unknown and hard to recover. Hence lighting modifications are only made in the spectral domain. A conventional approach to discount the illumination uses the inverse of the average color value to scale the color values in three channels independently[4] based on the "gray world" assumption. Alternatively, the scaling factors are determined by specifying a reference color in the image as white. This color balance problem is very similar to find some illuminant invariance in the color constancy. Subspace based approaches have been demonstrated to yield satisfied[1,2,7]. In this paper, we use the subspace approximation to derive the color correction operations, which are used to compensate lighting changes for dichromatic surfaces.

2. Background and Assumptions

Color formation is a combination of physical processes of light interaction with environment and the spectral sampling during the image capture process[11]. If the light entering the camera directly from the light source is negligible, the light reflected from a surface is:

$$Lr(\omega r, \lambda) = \int_{\Omega i} \rho(\omega i, \omega r, \lambda) Li(\omega i, \lambda)(n \cdot \omega i) d\omega i \quad (1)$$

Where n is the surface normal at a surface point imaged at a pixel. ωi and ωr are solid angles (or directions) of the incident and reflected light to the eye or camera at that point, Li and Lr are the incident and reflected radiance of the light at this surface point, λ is the wavelength, and ρ is the Bidirectional Reflectance Distribution Function (**BRDF**) of the surface[10]. **BRDF** is a material property, which is in general a function of ωi, ωr and λ. The measured triplet values in red, green and blue channels at each pixel from a digital camera are[10]:

$$\begin{pmatrix} r \\ g \\ b \end{pmatrix} = \frac{\pi}{4}\left(\frac{D}{f}\right)^2 \cos^4\alpha \begin{pmatrix} \int R(\lambda) Lr(\omega r, \lambda) d\lambda \\ \int G(\lambda) Lr(\omega r, \lambda) d\lambda \\ \int B(\lambda) Lr(\omega r, \lambda) d\lambda \end{pmatrix} \quad (2)$$

Where $R(\lambda)$, $G(\lambda)$ and $B(\lambda)$ are the spectral response functions of the digital camera, D and f are the aperture size and the focal length of the camera, α is the angle between ωr and the optical axis of the camera.

When lighting condition $Li(\omega i, \lambda)$ changes, the color value at each pixel will change correspondingly. It is very difficult to predict this change in general due to the integration in both spatial and spectral domains. To make this problem more tractable, the following assumptions are made in our method:

- Direct and Separable Lighting: We assume there is only one dominant light source in the scene. The other lights and the inter-reflections among surfaces only contribute a negligible amount of illumination. Furthermore, the light comes from the light source can be factored into spatial and spectral components. i.e. $Li\ (\omega i, \lambda) = Li(\omega i)\ Li(\lambda)$.

- All surfaces in the images are dichromatic. The **BRDF** of a dichromatic surface has a diffuse and a specular component. The diffuse component ρ_d is isotropic and changes the spectral content of an incident light, while the specular component ρ_s is highly directional and does not change the spectrum of the incident light[6,10,13]. i.e. $\rho_d\ (\omega i,\omega r,\lambda)= \rho_d\ (\lambda),\quad \rho_s(\omega i,\omega r,\lambda)= \rho_s(\omega i,\omega r)$
- The spectral response functions of the digital camera used to capture the image are known.
- The lighting modification is made only with respect to the changes in the spectrum of the light, whereas its spatial distribution is kept fixed.

Under these conditions, the color value at each pixel (x,y) is:

$$\mathbf{I}(x,y) = m_s(x,y)\mathbf{V_s} + m_d(x,y)\mathbf{V_d} \tag{3}$$

$\mathbf{I}$ is used to represent $(r,g,b)^T$, $\mathbf{V_s}$ and $\mathbf{V_d}$ are the specular and the diffuse color vectors defined as:

$$\mathbf{V_s} = \begin{pmatrix} \int R(\lambda)Li(\lambda)d\lambda \\ \int G(\lambda)Li(\lambda)d\lambda \\ \int B(\lambda)Li(\lambda)d\lambda \end{pmatrix},\quad \mathbf{V_d} = \begin{pmatrix} \int R(\lambda)\rho_d(\lambda)Li(\lambda)d\lambda \\ \int G(\lambda)\rho_d(\lambda)Li(\lambda)d\lambda \\ \int B(\lambda)\rho_d(\lambda)Li(\lambda)d\lambda \end{pmatrix} \tag{4}$$

m_s and m_d are their corresponding shading terms:

$$ms(x,y) = \frac{\pi}{4}\left(\frac{D}{f}\right)^2 cos^4\alpha \int_{\Omega i} \rho s(\omega i, \omega r,) Li(\omega i)(n\cdot \omega i)d\omega$$

$$md(x,y) = \frac{\pi}{4}\left(\frac{D}{f}\right)^2 cos^4\alpha \int_{\Omega i} Li(\omega i)(n\cdot \omega i)d\omega \tag{5}$$

When the light spectrum changes, the color value becomes:

$$\mathbf{I'}(x,y) = m_s(x,y)\mathbf{V'_s} + m_d(x,y)\mathbf{V'_d} \tag{6}$$

Where $\mathbf{V'_s}$ and $\mathbf{V'_d}$ are defined similar as $\mathbf{V_s}$ and $\mathbf{V_d}$, but with a different light spectrum $Li'(\lambda)$. m_s and m_d do not change since the spatial pattern of the illumination is assumed to be fixed.

3. Photographic Modification

If surfaces are purely dichromatic, $\mathbf{V_s}$ and $\mathbf{V_d}$ can be evaluated via the color histogram analysis[7,13,14]. We have tried two schemes to determine $\mathbf{V_s}$, one is the plane intersecting technique proposed by Tominiga[14], and another is to use a calibrated material with a known reflectance spectrum[10]. Once $\mathbf{V_s}$ is determined, $\mathbf{V_d}$ can be derived in a maximal saturation angle criterion[12].

Given $\mathbf{V_s}$, the lighting spectrum $Li(\lambda)$ can be estimated via either subspace approximations[1,14], or likelihood methods[10], or a recent developed color correlation technique[3]. The spectrum of the diffuse reflectance $\rho\,(\lambda)$ can also be estimated with $\mathbf{V_s}$ and $\mathbf{V_d}$[1,2,7]. It is shown in the Appendix that, a specular color correction operator $\mathbf{T_s}$ and a diffuse color correction operator $\mathbf{T_d}$ can be derived without $\rho\,(\lambda)$ being explicitly solved. $\mathbf{T_s}$ and $\mathbf{T_d}$ are the operators used to predict the changes in the orientations and magnitudes of color vectors $\mathbf{V_s}$ and $\mathbf{V_d}$ respectively under illumination changes, i.e.

$$\mathbf{V'_s} = \mathbf{T_s}\,\mathbf{V_s},\quad \mathbf{V'_d} = \mathbf{T_d}\,\mathbf{V_d} \tag{7}$$

This is illustrated in Figure 1. Thus we get

$$\mathbf{I'}(x,y) = \mathbf{T_s}[m_s(x,y)\mathbf{V_s}] + \mathbf{T_d}[m_d(x,y)\mathbf{V_d}] \tag{8}$$

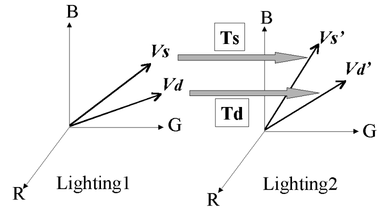


Figure 1. The change of specular and diffuse color vectors under the change of the illumination spectra.

Hence, the color prediction at each pixel of the image under the new lighting condition is the superposition of $\mathbf{T_s}$ being applied to the specular component of the original image, and $\mathbf{T_d}$ being applied to the diffuse component.

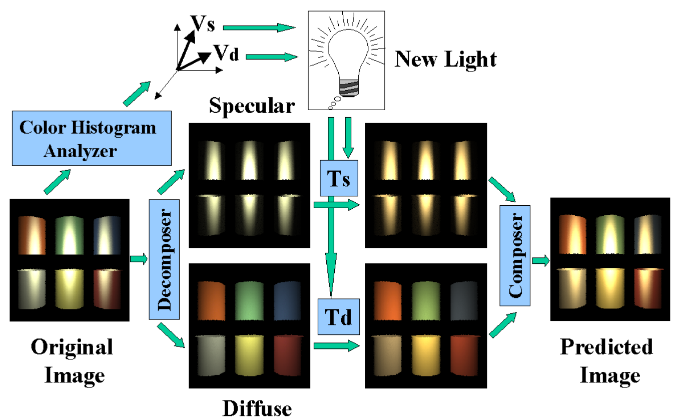


Figure 2.The procedure of the photographic modification.

The entire lighting modification procedure is outlined in Figure 2. First, the specular and the diffuse color vectors $\mathbf{V_s}$ and $\mathbf{V_d}$ are obtained by the color histogram analysis in the dichromatic reflection model. Then $\mathbf{V_s}$ is used to estimate the illumination spectrum $\mathbf{L}$ via a subspace analysis. $\mathbf{T_s}$ and $\mathbf{T_d}$ are derived with $\mathbf{L}$, the new specified lighting spectrum $\mathbf{L'}$, and a carefully chosen basis functions $\mathbf{B}$ of the reflectance spectra. The original color image is also decomposed into a specular and a diffuse component image with $\mathbf{V_s}$ and $\mathbf{V_d}$, which are color corrected by $\mathbf{T_s}$ and $\mathbf{T_d}$ respectively. Finally, the two modified images are combined together to yield a predicted image under the new specified lighting condition.

4. Experiments and Results

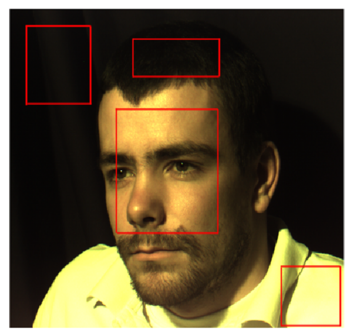
In order to evaluate the effectiveness of our proposed algorithm, we have conducted an experiment by taking a portrait image of a human subject using a Kodak DCS420 camera with known spectral responses. Two well-controlled light sources, a tungsten halogen photo lamp and an electronic flash light, were used as light sources in the measurements. The spectra of these two light sources were measured by a gonioreflectometer, and they were positioned carefully at the same spatial location, with only one turned on at each time.

Figure 3. Color correction for illumination changes with real photographic images. The top left image is taken under the electronic flash light illumination, while the top right one is taken under the tungsten light illumination. Starting with the image under the flash light, WBM (bottom left) and the dichromatic method (DM) (bottom right) are used to predict the image under the tungsten light.

The top two images shown in Figure 3 are the portrait images taken under these two lights. The image taken under the flash light (top left) is used as the input in the entire color correction procedure to predict the image taken under the tungsten light (top right). The bottom left image and the bottom right image shown in the same figure are the resulting predicted images when the white balance method (WBM) and the proposed dichromatic based modification method (DM) are applied respectively. The two images in Figure 4 are the error images formed by taking the color ratio between each predicted image with the measured image under the tungsten light. The chromatic information in the error images is used to examine the performance of the color correction. The achromatic pixels indicate that the chromatic vectors of the predicted and the measurement are close. White indicates perfect correspondence. It is shown in the facial and shirt regions of the error images that, most predicted colors from our proposed method are much closer to the white color than those resulted from WBM, showing more accuracy in the lighting prediction of DM. However, since our method mainly corrects the diffuse colors according to the skin-tone reflectance spectrum (via choosing basis functions well spanned for skin tones reflectance) in this example, it gives little improvement in the hair and background cloth regions where the reflectance has a large deviation from the skin-tone.

Figure 4. Error images of the WBM (left) and the new proposed DM method (right)

A detail comparison of errors is shown in Figure 5 with four outlined regions. Here the error metric D_θ is the chromatic angular difference between the predicted color and the measured color, while D_I is the relative magnitude difference between the predicted color and the measured color[10]. The tabulated data shows a more accurate prediction of DM in the face and shirt regions, while little improvement in the hair and cloth region. This agrees with the results from Figure 4.



	WBM		**DM**	
Region	**D_θ(°)**	**D_I(%)**	**D_θ(°)**	**D_I(%)**
Face	**4.05**	**14.9**	**1.55**	**2.90**
Shirt	**3.55**	**8.85**	**2.65**	**5.30**
Hair	**8.60**	**55.3**	**9.65**	**4.45**
Cloth	**10.3**	**86.9**	**12.3**	**74.0**

Figure 5. Four regions are selected in the area of the face, the shirt, the hair of the subject, and the background cloth. These regions are used to compare the errors between the predicted results from WBM and DM with the measurement.

5. Conclusion and Future Research

We have presented a new algorithm to modify the colors of dichromatic objects in images, predicting their appearance under different illumination spectra. We have demonstrated in a photographic image that this method yields convincing results. Nevertheless, there are difficulties when this method is applied in a general lighting modification. This is because: (1) The direct lighting assumption is violated in most scenes. Global illumination poses a major problem in this problem, making it impossible to separate the colors of two reflection components and to predict the color changes under the change of illuminations. (2) The decomposition of diffuse and specular reflection colors may fail when the surfaces in the scene are not purely dichromatic. (3) The three-basis subspace approximation of the spectra of the surface reflectance may not be sufficiently accurate[5]. (4) The specular and diffuse color vectors may not be extracted reliably when the acquired color signals in the image are too noisy[10].

However, this method still has great potential. In many digital photography applications such as studio portrait shooting, or outdoor photography under the sunlight, a single source usually dominates the illumination, the direct lighting approximation suffices. The color correction can be improved through more reliable estimation of the spectra of surface reflectance. One approach is to acquire data with more than three-color channels and estimate the spectra with more number of basis functions. This can be realized either by using a digital camera with multiple filters[9], or by taking another image of the same scene with an attached flashing light on the camera. Another approach is to estimate the spectra with more constrained sets of basis functions based on some additional knowledge about the surface material[10]. Furthermore, we can combine this spectral based method with the inverse lighting and re-lighting technique[8]. With the additional three-dimensional information on geometry of objects and the environment, we can fully conduct a physically based lighting modification in both spectral and spatial domains.

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References

1. R. Bajcsy, S. W. Lee, A Leonardis, Detection of diffuse and specular interface reflections and inter-reflections by color image segmentation. International Journal of Computer Vison, 17(3), pages 241-272 (1996).
2. M. D'Zmura. Color constancy: surface color from changing illumination. *Journal of Optical Society*, American A, Vol. 9, pages 490-493 (1992).
3. G. D. Finlayson, P.M.Hubel, S. Hordley, Color by Correlation. *Fifth Color Imaging Conference: Color Science, System, and Application*, pages 1-6, (1997).
4. G. D. Finalson, M.Drew. White-point preserving color correction. *Fifth Color Imaging Conference: Color Science, System, and Application*, pages 258-261 (1997)
5. B. Funt. Linear models and computational color constance. *Fourth Color Image Conference: Color Science, System, and Application*, pages 26-29, (1996).
6. G. J. Klinker. *A Physical Approach to Color Image Understanding.* A. K. Peters, Ltd, Wellesley, MA, (1993).
7. L. T. Maloney, B. A. Wandell. Color constancy: a method for recovering surface spectral reflectance. *Journal of Optical Society*, American A, Vol. 3, pages 29-33, (1993).
8. S. R. Marschner, D. P. Greenberg. Inverse Lighting for Photography, *Fifth Color Imaging Conference: Color Science, System, and Application*, page 262-265, (1997).
9. S.N. Pattanaik, J. A. Ferwerda, K. E. Torrence, D. P. Greenberg, Validation of Global Illumination Simulations through CCD Camera Measurements. *Fifth Color Imaging Conference: Color Science, System and Application*, pages 250-253 (1997).
10. L. Peng. *The Color Histogram and its applications in Digital Photography, Ph.D. Dissertation.* Cornell University (1998).
11. L. Peng, E. P. F. Lafortune, D. P. Greenberg, I. Sobel. Use of Computer Graphic Simulation to explain Color Histogram Structure. *Fifth Color Imaging Conference: Color Science, System and Application*, pages 187-192, (1997).
12. Y. Sato and K. Ikeuchi. Reflectance analysis for 3D computer graphics model generation. Graphical Models and Image Processing, vol. 58, pages 437-451 (1996).
13. S. A. Shafer. Using color to separate reflection components. *Color Research and Application*, 10(**4**), pages 210-218, (1985).
14. S. Tominaga, Realization of Color Constancy Using the Dichromatic Reflection Model. *2nd Color Imaging Conference: Color Science, System and Application*, pages 37-40 (1994).

Appendix

If we use **R,** a 3xn matrix to represent the spectral sample of the response functions $(R,G,B)^T$, an n-vector ρ to represent the spectral sample of diffuse reflectance, and **L,** either in a n-vector or a nxn diagonal matrix form, to represent the spectral sample of the illumination, then Equation (4) can be rewrite as

$$\mathbf{V_s = RL}, \quad \mathbf{V_d = RL}\rho \tag{A1}$$

Similarly, under the new lighting **L',** the color vectors are

$$\mathbf{V'_s = RL'}, \quad \mathbf{V'_d = RL'}\rho \tag{A2}$$

In a spectral subspace spanned by the column vectors of **B,** an nx3 matrix, $\rho = \mathbf{Bb}$, where **b** is a 3-vector representing the weight coefficients of these three basis vectors. Then,

$$\mathbf{V_d = RLBb}, \tag{A3}$$

As long as (**RLB**) is non-singular,

$$\mathbf{b = (RLB)^{-1}V_d} \tag{A4}$$

Hence

$$\mathbf{V'_d = (RL'B)(RLB)^{-1}V_d} \tag{A5}$$

If we define $\mathbf{T_d = (RL'B)(RLB)^{-1}}$, then $\mathbf{V'_d} = \mathbf{T_d V_d}$. $\mathbf{T_d}$ is a diffuse color correction operator.

Also, with **L** and **L'** known, we can relate the two by a diagonal transformation matrix **D**:

$$\mathbf{L' = DL} \tag{A6}$$

If we can find a 3x3 matrix **K,** s.t

$$\mathbf{RD = KR} \tag{A7}$$

Then

$$\mathbf{V'_s = RDL = KRL = K\,V_s} \tag{A8}$$

This **K** is just the specular color correction operator $\mathbf{T_s}$. It is not difficult to show that when $\mathbf{K} = (\mathbf{RDR}^T)(\mathbf{RR}^T)^{-1}$, Equation (A6) is satisfied. So, the specular color correction operator is: $\mathbf{T_s} = (\mathbf{RDR}^T)(\mathbf{RR}^T)^{-1}$.