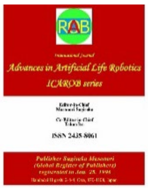
SUGISAKA MASANORI

Journal of Advances in Artificial Life Robotics
Vol. 1(3); December (2020), pp. 122–127
ON LINE ISSN 2435-8061; ISSN-L 2435-8061
https://alife-robotics.org/jallr.html



Research Article

Specular Reflection Analysis and Illumination Manipulation of Still Images with Single Multicolor Object

Hsuan T. Chang, Wei-Hsiu Chang
Photonics and Information Laboratory, Department of Electrical Engineering, National Yunlin University of Science and Technology, 123, Section 3,University Road, Douliu, Yunlin 64002, Taiwan

ARTICLE INFO

Article History

Received 11 November 2019
Accepted 10 August 2020

Keywords

Chromaticity
Dichromatic-based model
Specular removal
Color consistence
Virtual illumination

ABSTRACT

An illumination manipulation scheme for a single object in still images is proposed in this paper. By using the dichromatic-based model, the reflection component can be resolved through a single-image specular reflection removal method with the characteristics of color constancy. Then, virtual illumination effect can be made through the recombination with the reflection component. The scenery illumination can be estimated using the proposed automatic method without knowing the illumination spectra, three-dimensional object modeling, or texture databases. Experimental results show that the method is useful for handling the images with a single multicolor object in scenes.

1. Introduction

Establishing the relighting in the computer graphics needs the provision of the light sources from different directions. Using only one single input image is not enough to complete the relighting of the objects in the image. In this paper, we propose a method which can modify the illumination conditions in images. By separating the specular reflection and automatically evaluating the illumination in the image, the reconstruction of 3-D scene can be discarded and we can perform realistic control on illumination colors in images.

In recent research about specular highlight removal [1], most methods on separating the specular reflection components in a single image are based on the reflection model established by Shafer [2]. The reflection model assumes the complex light paths as a simple reflection component and analyzes the highlight information based on polarized photography. Thereafter, more related methods have been proposed. For example, the T-shape image color space proposed by Shafer and Klinker can be used to analyze the neighboring pixels of an object [3]. In this method, the reflected specular and diffused colors are viewed as orthogonal color vectors. However, in the bright image textures, the linear distribution model is hardly used to estimate the vectors in the color space.

The specular-free image (SFI) method determines the diffused components by estimating either the intensity or chromaticity of the image. Tan's method [4] generates the SFI by analyzing the maximum chromaticity space at first. In this method, the specular reflection is considered as the chromaticity deviation and the maximum chromaticity is set as the pixel common chromaticity. When the maximum chromaticity is extracted and discarded, the specular component can be removed. However, in a non-single color image, different maximum chromaticity in the chromaticity space for different textures could be observed. Therefore, the controversy exists on selecting the chromaticity. Yoon's specular-free two-band image (SFTBI) method [5], which uses the specular-invariant to determine the diffused reflection component, is thus proposed. A diffused reflection image with low chromaticity can be obtained. In addition, Shen proposed the modified specular-free image (MSFI) [6] method to improve Yoon's method.

Corresponding author's E-mail: htchang@yuntech.edu.tw, stire001@hotmail.com

The SFI method is usually used together with the neighboring region analysis. Although the SFI method usually cannot get precise component analysis during the separation process, SFI can easily obtain the result without specular components. The specular reflection pixels can be found by analyzing the difference between the SFI and the intrinsic image in the neighboring region. In Tan's method [4], the iteration process is used at low chromaticity range for both the SFI and normalized image. The high-quality or bright-color texture images can be successfully processed by setting regional chromaticity. Yoon and Shen proposed different mechanisms to improve the iteration efficiency. Other types of methods are based on the dichromatic reflection model. For example, Ping's inpainting method [7], which repairs the highlight points (also considered as region of interest, ROI). Rouf proposed the star filter to filter the highlight points based on the structural characteristics [8]. Tan et. al. also proposed a single integrated method to estimate illumination chromaticity from single-colored and multicolored surfaces [9]. Different from the conventional dichromatic-based methods, the proposed method deals only with rough highlight regions does not segment the colors inside them.

Recently, more studies have been proposed and applied to various applications. Akashi and Okatani proposed a novel method [10], which can simultaneously perform the estimation of object colors and the separation of specular components based on a modified version of sparse non-negative matrix factorization. Wang et. al. proposed a novel and accurate approach to remove the specular effect and improve image quality by using the light field camera [11]. Suo et. al. proposed a method to remove the specular highlight from a single image and to especially target for wide applicability to the large variety of nature scene [12]. To overcome the degradation problem in texture regions and the blocky effects in separating the specular reflection, Ren et. al. proposed a method in which the global color-lines constraint from the dichromatic reflection model is derived to recover specular and diffused components for texture images [13]. In order to remove the specular highlight reflections in facial images that may contain varying illumination colors, Lin et. al. proposed a method especially for handling partially saturated pixels, varying illumination colors, and ambiguities caused by the similarity between illumination chromaticity and diffuse chromaticity [14]. Guo et. al. proposed a sparse and low-rank reflection model to avoid the hue-saturation ambiguity in retrieving an SFI and to preserve scene details in images as much as possible.

In this paper, the proposed method mainly deals with the color constancy based on the chromaticity and integrated the methods of high-light removal proposed by Tan and Shan [4], [6] to achieve the reflection removal purpose. By providing the new RGB values in chromaticity, we can arbitrarily set the virtual illumination onto the object in the image. Moreover, the specular reflectivity of the object can be arbitrarily increased or decreased.

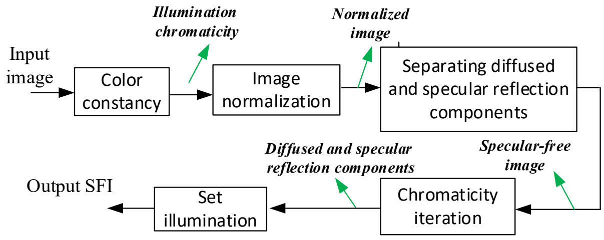


Fig. 1: The system diagram of the proposed method.

2. Proposed Method

Figure 1 shows the system diagram of the proposed method. The proposed illumination estimation method is based on the inverse-intensity chromaticity space [9]. In this space, the specular component will be labeled and then be transferred to the Hough space to statistically determine the corresponding chromaticity direction. Illumination estimation mainly aims to provide the correct intensity information during the separation of reflection components. The intensities of non-white light illuminations are inhomogeneous while changing the intensity. Therefore, we assume that the illumination transformation is correctly estimated using the same compensation mechanism.

The dichromatic-based model is used to determine the diffused reflection components. The SFI can be obtained using Tan's method [9]. Then the improved SFI, called the simplified mechanism of SFI can achieved. First, Tan's method mentioned that the image intensity can be divided into two parts according to the dichromatic-based model. That is,

$$\mathbf{I}(\underline{\mathbf{x}}) = w_d \int_{\Omega} S(\lambda)E(\lambda)\mathbf{q}(\lambda)d\lambda + w_S \int_{\Omega} E(\lambda)\mathbf{q}(\lambda)d\lambda, \quad (1)$$

where $\mathbf{I}(\underline{\mathbf{x}}) = \{I_r, I_g, I_b\}$ denotes the color vector of image intensity recorded by a camera. $\underline{\mathbf{x}}=\{x,y\}$ denotes the 2D coordinates, $\mathbf{q} = \{q_r, q_g, q_b\}$ denotes the 3D vector of sensor sensitivity. $S(\lambda)$ and $E(\lambda)$ denote the diffused and the illumination spectral distributions, respectively. w_d and w_S denote for the weighting factors of specular and diffuse reflection, respectively. The values depend on the geometric structure in the regional coordinate $\underline{\mathbf{x}}$. Image intensity is within the visible spectrum (Ω). As shown in Eq. (1), the dichromatic-based model describes the image pixel intensity by separating them into two reflection components: $w_d \int_{\Omega} S(\lambda)E(\lambda)\mathbf{q}(\lambda)d\lambda$, which denotes the diffused reflection components, and $w_S \int_{\Omega} E(\lambda)\mathbf{q}(\lambda)d\lambda$, which denotes the specular reflection components in an image. Diffused component includes the reflection spectrum of the object, while the specular one just depends on the illumination. The specular and diffused reflection components are two independent color vectors, which can be expressed as two bold-face characters, **B** and **G**, respectively. We also assume that the specular components are uniformly distributed in the scene so that the illumination colors are independent to the regional coordinates. The intensity equation of the original image can be replaced a simplified combination:

$$\mathbf{I}(\underline{\mathbf{x}}) = w_d\mathbf{B}(\underline{\mathbf{x}}) + w_S\mathbf{G}, \quad (2)$$

where

$$\mathbf{B}(\underline{\mathbf{x}}) = \int_{\Omega} S(\lambda)E(\lambda)\mathbf{q}(\lambda)d\lambda, \quad (3)$$

$$\mathbf{G} = \int_{\Omega} E(\lambda)\mathbf{q}(\lambda)d\lambda. \quad (4)$$

In order to analysis the relationship between the reflection components and scaling factor. The image chromaticity is defined by using the normalized RGB components. Here, the chromaticity (σ), diffuse chromaticity (Λ), and specular chromaticity (Γ) are defined as

$$\boldsymbol{\sigma}(\underline{\mathbf{x}}) = \frac{\mathbf{I}(\underline{\mathbf{x}})}{I_r(\underline{\mathbf{x}})+I_g(\underline{\mathbf{x}})+I_b(\underline{\mathbf{x}})}, \quad (5)$$

$$\boldsymbol{\Lambda}(\underline{\mathbf{x}}) = \frac{\mathbf{B}(\underline{\mathbf{x}})}{B_r(\underline{\mathbf{x}})+B_g(\underline{\mathbf{x}})+B_b(\underline{\mathbf{x}})}, \quad (6)$$

$$\boldsymbol{\Gamma} = \frac{\mathbf{G}}{(G_r+G_g+G_b)}, \quad (7)$$

Substituting Eqs. (5) and (6) into Eq. (2), the chromaticity equation becomes

$$\mathbf{I}(\underline{\mathbf{x}}) = m_d(\underline{\mathbf{x}})\boldsymbol{\Lambda}(\underline{\mathbf{x}}) + m_s(\underline{\mathbf{x}})\boldsymbol{\Gamma}, \quad (8)$$

where

$$m_d(\underline{\mathbf{x}}) = w_d\{B_r, B_g, B_b\}, \quad (9)$$

$$m_s(\underline{\mathbf{x}}) = w_s\{G_r, G_g, G_b\}. \quad (10)$$

In the reflection model shown in Eq. (1), in which only the specular reflection component exists (w_d=0), **Γ** will be independent of the specular geometrical parameter w_S. In the definition on chromaticity, the range of image chromaticity, diffuse chromaticity, and specular chromaticity are all within the range {0, 1}. That is, $\{\sigma_r+\sigma_g+\sigma_b\} = \{\Lambda_r+\Lambda_g+\Lambda_b\} = \{\Gamma_r+\Gamma_g+\Gamma_b\} = 1$. The illuminant chromaticity is estimated based on the color constancy method in Ref. [2] to evaluate the chromaticity $\boldsymbol{\Gamma}^{est} = \{\Gamma_r^{est}, \Gamma_g^{est}, \Gamma_b^{est}\}$. Assume that the evaluated chromaticity is correct. The image with corrected illumination is defined as a normalized image:

$$\mathbf{I}'(\underline{\mathbf{x}}) = m_d'(\underline{\mathbf{x}})\boldsymbol{\Lambda}'(x) + \frac{1}{3}m_s'(\underline{\mathbf{x}}), \quad (11)$$

where

$$m_d(\underline{\mathbf{x}})\boldsymbol{\Lambda}(\underline{\mathbf{x}}) = [m_d'(\underline{\mathbf{x}})\boldsymbol{\Lambda}'(\underline{\mathbf{x}})]\boldsymbol{\Gamma}^{est}, \quad (12)$$

$$m_s(\underline{\mathbf{x}})\boldsymbol{\Gamma} = \left[\frac{1}{3}m_s'(\underline{\mathbf{x}})\right]\boldsymbol{\Gamma}^{est}. \quad (13)$$

The normalized image can be denoted as $\mathbf{I}'(\underline{\mathbf{x}}) = \frac{\mathbf{I}(\mathbf{x})}{\boldsymbol{\Gamma}^{est}}$. The normalized illumination color is $\frac{\boldsymbol{\Gamma}}{\boldsymbol{\Gamma}^{est}} = \{1,1,1\}$. In $\mathbf{I}'(\underline{\mathbf{x}})$, $\boldsymbol{\Gamma}' = \{\frac{1}{3}, \frac{1}{3}, \frac{1}{3}\}$ and $3m_s = m_s'$. Normalized image will be considered as a diffused reflection image illuminated by a standard white light.

Since Tan's specular-to-diffuse mechanism does not generate a real diffuse image, the image can be seemed as a fake diffused reflection image. In this mechanism, the maximum chromaticity is used. The definition of maximum chromaticity of image pixels is as follow

$$\tilde{\sigma}'(\underline{\mathbf{x}}) = \frac{\max(I'_r(\underline{\mathbf{x}}), I'_g(\underline{\mathbf{x}}), I'_b(\underline{\mathbf{x}}))}{I'_r(\underline{\mathbf{x}})+I'_g(\underline{\mathbf{x}})+I'_b(\underline{\mathbf{x}})}, \quad (14)$$

where $(I'_r(\underline{\mathbf{x}}), I'_g(\underline{\mathbf{x}}), I'_b(\underline{\mathbf{x}}))$ is obtained in the normalized image, σ′ denotes the chromaticity of the normalized image. Note that $\tilde{\sigma}'$ is different from σ' and the range of $\tilde{\sigma}'$ is not between 0 and 1. With Eqs. (11) to (13), the maximum chromaticity of image pixels in Eq. (14) can be rewritten as:

$$\tilde{\sigma}'(\underline{\mathbf{x}}) = \frac{m_d'(\underline{\mathbf{x}})\tilde{\Lambda}'(\underline{\mathbf{x}})+\frac{1}{3}m_s'(\underline{\mathbf{x}})}{m_d'(\underline{\mathbf{x}})[\Lambda_r'(\underline{\mathbf{x}}), \Lambda_g'(\underline{\mathbf{x}}), \Lambda_b'(\underline{\mathbf{x}})]+m_s'(\underline{\mathbf{x}})}. \quad (15)$$

By setting $\tilde{\Lambda}' = \max(\Lambda'_r, \Lambda'_g, \Lambda'_b)$, both m_d' and m_s' can also be determined. Since the maximum chromaticity of diffused reflection is usually higher than that of specular reflection and, in generally, $\tilde{\Lambda}' > \frac{1}{3}$, and

$$\tilde{\sigma}'_{diff} > \tilde{\sigma}'_{spec}, \quad (16)$$

$$\frac{\tilde{\Lambda}'}{[\Lambda_r', \Lambda_g', \Lambda_b']} > \frac{m_d'\tilde{\Lambda}'(\underline{\mathbf{x}})+\frac{1}{3}m_s'}{m_d'[\Lambda_r', \Lambda_g', \Lambda_b']+m_s'}. \quad (17)$$

In the normalized image, $(\Lambda_r'+\Lambda_g'+\Lambda_b')$=1. Removing the pixel $(\underline{\mathbf{x}})$ and substituting m_s' ($m_s'=m_d'(\frac{\tilde{\Lambda}-\tilde{\sigma}'}{\tilde{\sigma}-\frac{1}{3}})$) into Eq. (17), we can finally obtain the equation that can represent the relationship between the image chromaticity and illumination chromaticity:

$$\tilde{I}'(\underline{\mathbf{x}}) = m_d'\left(\tilde{\Lambda}' - \frac{1}{3}\right)\left(\frac{\tilde{\sigma}'}{\tilde{\sigma}'-\frac{1}{3}}\right). \quad (18)$$

In the above equation, m_d' is computed by assuming the same chromaticity. In the specular pixel $(\underline{\mathbf{x}}_1)$ and diffused pixel $(\underline{\mathbf{x}}_2)$, the same chromaticity is used such that $\tilde{\Lambda}'(\underline{\mathbf{x}}_1) = \tilde{\Lambda}'(\underline{\mathbf{x}}_2) = \tilde{\sigma}'(\underline{\mathbf{x}}_2)$ ($m_s'=m_d'$ here). We can determine m_d' by using:

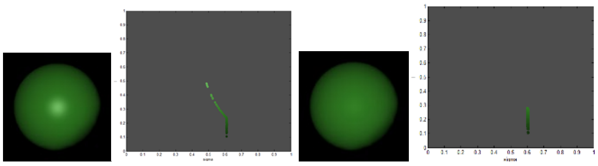
$$m_d'(\underline{\mathbf{x}}_1) = \frac{\tilde{I}'(\underline{\mathbf{x}}_1)[3\tilde{\sigma}'(\underline{\mathbf{x}}_1)-1]}{\tilde{\sigma}'(\underline{\mathbf{x}}_1)[3\tilde{\Lambda}'(\underline{\mathbf{x}}_1)-1]}. \quad (19)$$

The final result is

$$m_s'(\underline{\mathbf{x}}_1) = [I'_r(\underline{\mathbf{x}}_1) + I'_g(\underline{\mathbf{x}}_1) + I'_b(\underline{\mathbf{x}}_1)]m_d'(\underline{\mathbf{x}}_1), \quad (20)$$

where the diffused reflection component is

$$m_d'(\underline{\mathbf{x}}_1)\tilde{\Lambda}'(\underline{\mathbf{x}}_1) = \tilde{I}'(\underline{\mathbf{x}}_1) - \frac{m_s'(\underline{\mathbf{x}}_1)}{3}. \quad (21)$$



(a) (b) (c) (d)

Fig. 2: (a) The original image; (b) Projection of pixel intensity in (a) into the chromatic space ($\tilde{\sigma}'$, $\tilde{I}'$); (c) The SFI with the maximum chromaticity; (d) The projection of pixel intensity in (c) into the chromatic space ($\tilde{\sigma}'$, $\tilde{I}'$).

Figures 2(a) and 2(b) show an input image and its 2D projection of the maximum chromatic intensity $\tilde{\sigma}'$ and intensity $\tilde{I}'$, respectively. In Fig. 2(b), the x axis denotes the maximum chromaticity intensity $\tilde{\sigma}'$, while the y axis denotes the intensity $\tilde{I}'$. Fig. 2(c) shows the SFI obtained by suing Tan's method with setting the $\tilde{\Lambda}' = \max(\Lambda'_r, \Lambda'_g, \Lambda'_b)$ in the maximum chromaticity for all image pixels. In Fig. 2(d), the SFI specular component has the same chromaticity with the diffused one.

Yoon proposed a simplified SFI method based on the property of invariant specular reflection, whose mechanism is shown as follows:

$$\mathbf{I}_{sf}(\underline{\mathbf{x}}) = \mathbf{I}'(\underline{\mathbf{x}}) - \mathbf{I}_{min}(\underline{\mathbf{x}}), \quad (22)$$

$$\mathbf{I}_{min}(\underline{\mathbf{x}}) = m_d\, \lambda_{min}(\underline{\mathbf{x}}) + \frac{1}{3} m_s'(\underline{\mathbf{x}}), \quad (23)$$

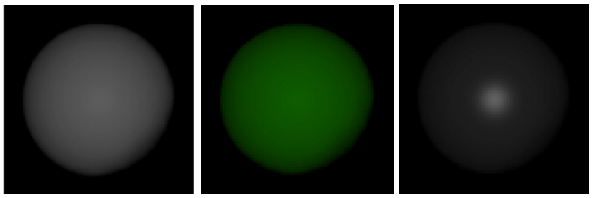
where $\mathbf{I}_{sf}$ presents SFI, $\mathbf{I}_{min}$ presents the minimum pixel value of the normalized image in RGB channels. Similarly, we assume that the specular reflection is also invariant in the HSV space:

$$\mathbf{I}_{min}(\underline{\mathbf{x}}) = \begin{cases} S = 0 \\ V = \min(I_r, I_g, I_b) \end{cases}. \quad (24)$$

Different from the Tan's method, we use the HSV color space to determine the SFI, which is shown in Fig. 3(b). The S and V components present the saturation and scalar intensity values, respectively. And the specular and diffused components of chromaticity are the same with that in the input image. By subtracting the change of specular component, the intensity of SFI shown in Fig. 3(a) will be a uniform intensity. Fig. 3(c) shows the invariant specular reflection part of the original image. The SFI component is determined as follows:

$$\mathbf{I}_{sf}(\underline{\mathbf{x}}) = m_d\left(\lambda(\underline{\mathbf{x}}) - \lambda_{min}(\underline{\mathbf{x}})\right). \quad (25)$$

The illumination setting for the final output SFI image is the last step. The user can define a new reflectivity by setting $\sum_{u\in\{r,g,b\}} \mathbf{\Gamma}^{set}$. That is, the separating specular and diffused reflections parts can be edited for the final combination. Finally, by replacing the original chromaticity with the new one $\mathbf{\Gamma}^{set} = \{\Gamma_r^{set}, \Gamma_g^{set}, \Gamma_b^{set}\}$, the final SFI image can be obtained.



(a) (b) (c)

Figure 3: (a) Intensity of SFI; (b) SFI; (c) invariant specular part $\mathbf{I}_{min}$.

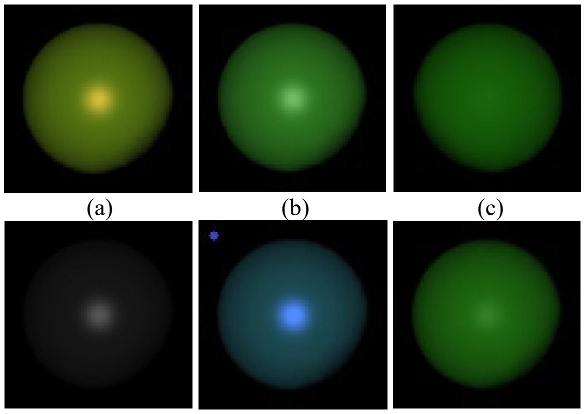


Fig. 4: (a) Image of a spherical object illuminated by a halogen lamp; (b) Normalized image with chromaticity RGB = (0.5324, 0.3077, 0.1594); (c) Separated diffused component; (d) Separated specular component; (e) The virtual image with the modified illumination chromaticity RGB = (0.2187, 0.2695, 0.7812); (f) Image with 50% reflectivity of the normalized image in (b).

3. Experiment Results

Suppose that the reflection light is generated from a fixed illumination in a scene. The proposed system can automatically detect the light source and then perform image normalization so that the image can be separated into the normalized image, diffused image, and specular image. By setting the chromaticity and the reflectivity, the user can obtain the image with a modified illumination color and with a stronger or weaker specular effect.

Figures 4 and 5 provide two demonstrations of the proposed method on resetting the chromaticity. Figure 4(a) shows an input image, in which the single-color spherical object is illuminated by a halogen lamp with the color temperature 4700 °K. Figure 4(b) shows the normalized image using the designated illumination chromaticity RGB = (0.5324, 0.3077, 0.1594). Figures 4(c) and 4(d) show the extracted diffused and specular components, respectively. Figure 4(e) shows the virtual image obtained by using the modified illumination chromaticity RGB = (0.2187, 0.2695, 0.7812). Figure 4(f) shows the image with 50% reflectivity of the normalized image shown in Figure 4(b). There are two colors in the spherical object shown in Figure 5(a). The illumination is the same as that in Figure 4(a). However, the designated illumination chromaticity RGB= (0.2187, 0.2695, 0.7812) in Figure 5(b) is different from that in Figure 4(b). By using the proposed method, Figures 5(c) and 5(d) show the separated diffused and specular components, respectively. Similarly, Figures 5(e) and 5(f) show the images obtained by using the modified illumination chromaticity RGB = (0.3046, 0.3007, 0.6992) and with 50% reflectivity of the normalized image in Figure 5(b), respectively.

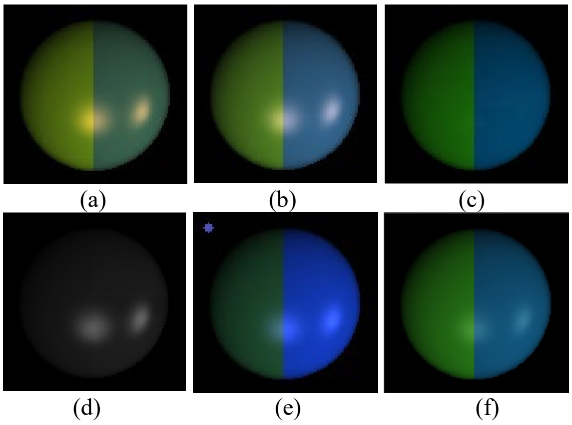


Fig. 5: (a) Dichromatic image of a spherical object illuminated by a halogen lamp; (b) Normalized image with chromaticity RGB = (0.2187, 0.2695, 0.7812); (c) Separated diffused component; (d) Separated specular component; (e) The virtual image with the modified illumination chromaticity RGB = (0.3046, 0.3007,0.6992); (f) Image with 50% reflectivity of the normalized image in (b).

Figures 6 and 7 shows the two examples with a more complicated geometric shape and with multi-color texture in the object, respectively. Figure 6(a) shows a single-color mask image illuminated by an incandescence bulb. Figure 6(b) shows the normalized image using the designated illumination chromaticity RGB = (0.3764, 0.3432, 0.294). Figures 6(c) and 6(d) show the extracted diffused and specular components, respectively. Figure 6(e) shows the virtual image obtained by using the modified illumination chromaticity RGB = (0.2109, 0.7773, 0.2265). Figure 6(f) shows the image with 200% reflectivity of the normalized image shown in Figure 6(a). In Figure 7(a), there are multiple colors in the object. The illumination is the same as that in Figure 6(a). Figure 7(b) shows the normalized image with the same chromaticity in Figure 7(a). By using the proposed method, Figure 7(c) and 7(d) show the separated diffused and specular components, respectively. Finally, Figure 5(e) show the images obtained by using the modified illumination chromaticity RGB = (0.7304, 0.2695, 0.4062) of the normalized image in Fig. 7(b).

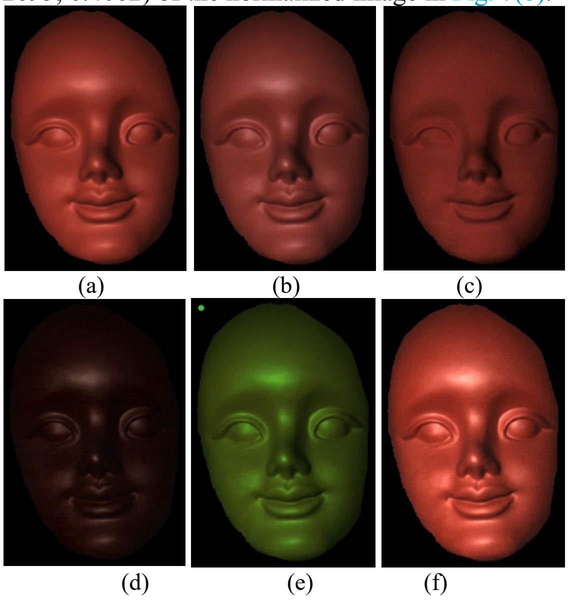


Fig. 6: (a) The image of a mask object illuminated by a incandescence bulb; (b) Normalized image with chromaticity RGB = (0.3764, 0.3432, 0.294); (c) Separated diffused component; (d) Separated specular component; (e) The virtual image with the modified illumination chromaticity RGB = (0.2109, 0.7773, 0.2265); (f) Image with 200% reflectivity of the original image in (a) .

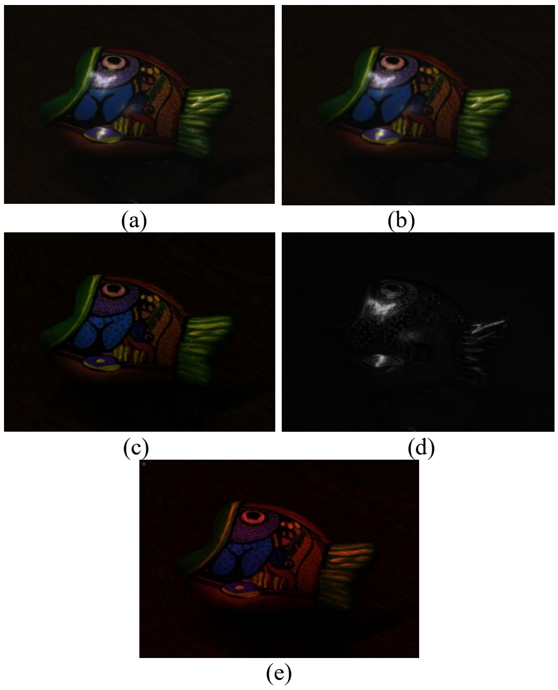


Fig. 7: (a) The image of a multicolor object illuminated by a incandescence bulb; (b) Normalized image with the same chromaticity in (a); (c) Separated diffused component; (d) Separated specular component; (e) The virtual image with the modified illumination chromaticity RGB = (0.7304, 0.2695,

0.4062) of the original image in (a).

4. Conclusion

We propose a method to simulate the object images under various illumination colors without constructing the 3-D model of the scene or requiring multiple input images. In addition, the reflectivity can also be assigned and be combined with the separated diffused components to obtain the designated image. Several examples with different objects are implemented in our experiments so that the effectiveness of the proposed method have been verified. The improved mechanism of SFI can accelerate the iteration process. Given an input image, the system will separate the specular and reflection components at first. Thus the high-light removal can be achieved. A graphical user interface has been implemented so that the users can easily manipulate the system to obtain the images with various illumination conditions such as the chromaticity and reflectivity.

Acknowledgements

This research was financially supported by Ministry of Science and Technology, Taiwan under the contract number MOST 109-2221-E-224-046-MY2.

References

1. A. Artusi, F. Banterle, and D. Chetverikov, “A survey of specularity removal methods,” Computer Graphics Forum, vol. 30, no. 8, pp. 2208-2230, 2011.
2. S.A. Shafer, “Using color to separate reflection components,” Color Research and Applications, vol. 10, pp. 210-218, 1985.
3. G.J. Klinker, S.A. Shafer, and T. Kannade, “A physical approach to color image understanding,” International Journal of Computer Vision, vol. 4, no. 1, pp. 7-38, 1990.
4. R.T. Tan and K. Ikeuchi, “Separating reflection components of textured surfaces using a single image,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 27, no. 2, pp. 178-193, 2005.
5. K.J. Yoon, Y. Choi, and I.S. Kweon, “Fast separation of reflection components using a specularity-invariant image representation,” 2006 IEEE International Conference on Image Processing (ICIP), pp. 973-976, 2006.
6. H.L. Shen and Q.Y. Cai, “Simple and efficient method for specularity removal in an image,” Applied Optics, vol. 48, no. 14, pp. 2711-2719, 2009.
7. T. Ping, S. Liny, L. Quanz, and H.Y. Shum, “Highlight removal by illumination-constrained inpainting,” Ninth IEEE International Conference on Computer Vision, vol. 1, pp. 164-169, 2003.
8. M. Rouf, R. Mantiuk, W. Heidrich, M. Trentacoste, and C. Lau, “Glare encoding of high dynamic range images,” 2011 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 289-296, 2011. R.T. Tan, K. Ikeuchi, and K. Nishino, “Color constancy through inverse-intensity chromaticity space,” Journal of the Optical Society of America, A, vol. 21, no. 3, pp. 321-334, 2004.
9. Y. Akashi and T. Okatani, “Separation of reflection components by sparse non-negative matrix factorization,” In: Cremers D., Reid I., Saito H., Yang MH. (eds) Computer Vision -- ACCV 2014. ACCV 2014. Lecture Notes in Computer Science, vol. 9007, pp 611-625, 2015.
10. H. Wang, C. Xu, X. Wang, Y. Zhang, B. Peng, “Light field imaging based accurate image specular highlight removal,” PLOS ONE, vol. 11, no. 6, e0156173, 2016.
11. J. Suo, D. An, X. Ji, H. Wang, and Q. Dai, “Fast and high quality highlight removal from a single image,” IEEE Transactions on Image Processing, vol. 25, no. 11, pp. 5441-5454, 2016.
12. W. Ren, J. Tian and Y. Tang, “Specular reflection separation with color-lines constraint,” IEEE Transactions on Image Processing, vol. 26, no. 5, pp. 2327-2337, 2017
13. C. Li, S. Lin, K. Zhou and K. Ikeuchi, “Specular Highlight Removal in Facial Images,” 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, 2017, pp. 2780-2789.
14. J. Guo, Z. Zhou, and L. Wang, “Single image highlight removal with a sparse and low-rank reflection model,” ECCV 2018, vol. 4, pp. 282-298, 2018

Authors Introduction

Dr. Hsuan T. Chang

He is a Professor in Department of Electrical Engineering, National Yunlin University of Science and Technology in Taiwan. He received his Ph.D degree from the Department of Electrical Engineering, National Chung Chen University, Taiwan in 1997. His research interests include digital image processing and optical information processing.

Mr. Wei-Hsiu Chang

He received his Master’s degree from the Department of Electrical Engineering, National Yunlin University of Science and Technology, Taiwan in 2003. He currently is a CAD engineering in Innolux Corporation, Jhunan, Taiwan.