Separation of Diffuse and Specular Reflection Components from Real-world Color Images captured under Flash imaging conditions

Nygel George Thomas, M. Zefree Lazarus, Supratim Gupta

Department of Electrical and Electronics Engineering
National Institute of Technology, Rourkela – 769008, INDIA
nygel93@gmail.com, zefree.lazarus@gmail.com, sgupta.iitkgp@gmail.com

ABSTRACT

Image processing applications like endoscopy, flash photography are prone to specularity reflection because of the usage of flash illumination during image acquisition. The formation of specularity reflection paralyzes the performance accuracy of many state-of-the-art feature detection algorithms. Specularity removal in case of real-world imaging conditions is further challenging when the source of illumination is unavailable. Literature suggests that chromaticity based reflection removal algorithms circumvent the illumination source dependency by transforming the pixels into the chromaticity-intensity plane and solving a fine-grained, least-squares problem of the dichromatic model. In this paper, we extend the existing chromaticity based removal approach to Hue-Saturation-Value color domain and explore its suitability in specularity removal under flash imaging conditions. Experimentation on MIT intrinsic database demonstrate that our approach achieves desirable reflection separation results with minimum execution time compared to the state of the art.

Keywords: Reflection, Saturation, Dichromatic reflection model, Color space.

I. INTRODUCTION

Specularity problem is one of the most challenging hindrances in applications like biomedical, computer vision, and digital photography. With the advent of smartphones, people can capture images in low illumination conditions by using mobile flash as a source of illumination [4,5,9]. Low illumination condition photography needs skill/expertise in capturing images, as the captured image can be flawed by the specularities formed due to the flash. Similarly, in the case of medical applications like endoscopy wherein a small camera with an attached flash is invasively navigated through the body of a patient---capturing video of the intended body organ for medical examination—suffers from information loss due to specularity effect. The specular problem resurfaces in many other image processing applications involving flash photography [11].

Variation in illumination level, relative positioning of ambient light source and the camera—result in specular reflections—which paralyze the performance accuracy of many existing state-of-the-art feature detection algorithms [19-21]. Therefore, mitigation of the specularity problem is a relevant and important challenge.

A. Specularity problem

Image formation of an object is governed by three processes:

- Illumination of the object by a light source.
- Reflection of light by the object.
- Detection of the reflected light.

Generally, illumination sources have uniformly distributed spectrum in all wavelengths of the visible region. Depending on the nature of the object, it absorbs a few wavelengths and reflects back its complementary colors—thereby providing a specific color. In literature, there are quite a few reflection models that define the image formation. Lambertian reflection model is one such fundamental reflection model. In this model, the light reflected by the material is assumed to be isotropic i.e. independent of the viewing direction. The materials which show this property are called matte materials. These matte materials do not show glare or mirror-like behavior called specularity. Many computer vision algorithms assume Lambertian surfaces and neglect the effect of specularity as outliers. In real-world images, these assumptions do not hold good because most of the objects photographed are not matte materials and therefore result in specularities. Due to this, the extent to which the Lambertian reflection model-based algorithms can be utilized is limited. A more realistic model that considers both highlights and anisotropic reflection is the Dichromatic Reflection Model (DRM) proposed by Shaufer [1].

Based on DRM, removing specularities from images can be coined as a problem of extraction of corrupted pixels from an image and converting it into a meaningful representation. Intrinsic image decomposition, a branch of Image processing deals with such information retrieval application algorithms. An exhaustive survey on the available literature is provided in [19]. Most of the available algorithms have high time complexity and therefore the adaptability of these algorithms for real-time applications is limited.

B. Contribution of this work

In this manuscript, we explore the DRM approaches and check the usability of the available state-of-the-art intrinsic decomposition methodologies in the context of specularity removal in real-time images. By extending the chromaticity based reflection removal approach proposed in [13] to Hue-Saturation-Value (HSV) color space we propose a simple yet practical way of suppressing the spectacle problem.

The paper is organized as follows: Section II describes the Dichromatic reflection model – its assumptions, advantageous and limitations, III describe the chromaticity based reflection removal algorithm, Section IV provides the proposed extension of the method discussed in Section III, Section V the experimentation, simulation results, and observations. The concluding remarks are given in Section VI.

II DICHROMATIC REFLECTION MODEL

Dichromatic reflection model (DRM) is a mathematical model which describes the reflection of light from a non-uniform surface. It focuses on the color aspect of reflection of light from a nonhomogeneous material illuminated by a uniform single source of light. Based on these assumptions, the model proposes that the total reflected light from a surface of uniform color is the weighted linear combination of the light reflected from the surface or interface of reflection which is called specular reflection and the complementary color reflected from the lattice of the material called diffuse reflection (see Fig. 1). The reflection from the surface will have mirror-like or specular features and the body component has diffusive properties which contribute mainly to the glow less color or matte of an object.

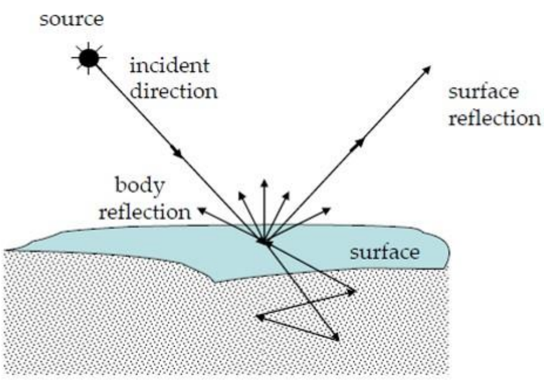

Fig. 1. Surface and body reflections of a surface.

The specular and diffusive components can be classified into:

- A univariable function of the wavelength of the illuminating source and gives the relative spectral power distribution.
- A multivariable function the geometrical properties which gives the geometrical scale factor.

The total radiance of reflected light from a surface,

$$L(\lambda, i, e, v) = L_i(\lambda, i, e, v) + L_b(\lambda, i, e, v) \quad \textbf{(1)}$$

By using the dichromatic mathematical model, we can further divide the body and surface into variable separable equations which depend on the geometry of the surface as well as the wavelength of the illuminant light. They are mutually independent. Thus the equation 1. can be further modified as,

$$L(\lambda, i, e, v) = m_i(i, e, v)c_i(\lambda) + m_b(i, e, v)c_b(\lambda) \quad \textbf{(2)}$$

where m_i and m_b are the scale factors which changes from point to point depending upon the geometry and C_i and C_b are the spectral power density over a range of wavelengths which does not depend on geometry. By using the linearity property as well as the variable separability of the body and surface reflection components [1] proposed that the pixels of a dichromatic surface will be confined to a parallelogram when plotted in RGB space (Fig. 2). This has been the groundwork for future research and modifications on the single image based separation.

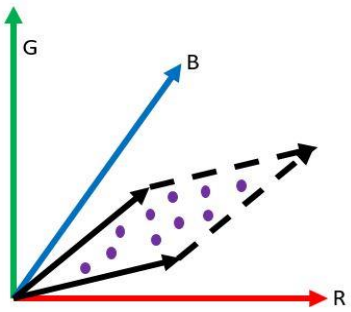

Fig. 2. Pixel values of a particular color align on the surface of a plane on a parallelogram in color space.

The DRM provides a basic mathematical model but does not provide an effective way of isolating the specular pixels. This aspect was further extended by Klinker et al. [6] by plotting the color histogram of all the pixels. The histogram forms a T-shaped distribution with highlight and matte component clustering into two side lobes of the T-shaped structure. But this approach is limited to dielectric objects as well as objects with uniform diffuse colors. Tan et al [2] extended the DRM approach and proposed a chromaticity based approach which separates the reflection components from a single image by mapping the pixels in a particular color space to maximum chromaticity-pixel intensity space.

A. Extension of DRM to pixels in a color space

As the DRM models color in terms of its reflection, it is obvious to extend the concept of dichromatic reflection to the popular color spaces. Moreover, when this model is fitted into a particular color space, the possibility of separation of its reflection components also has a pivotal role. This subsection gives the extension of DRM to the most used color space, viz. RGB space.

The spectral power density is the energy received on a surface per unit area per unit wavelength for a particular illumination. Using the spectral projections, the pixel values of the color images can be computed from the Spectral Power Distribution (SPD) of the measured light.

For a color camera, the color value of every pixel is given by the color matrix with the corresponding RGB components viz. r_x, g_x and b_x for a pixel. Color value matrix for an SPD $X(\lambda)$ and a camera sensitivity for R, G and B, $r(\lambda), g(\lambda)$and $b(\lambda)$ respectively is given by

$$C_x = \begin{bmatrix} r_x \\ g_x \\ b_x \end{bmatrix} \quad \textbf{(3)}$$

where $r_x = \int x(\lambda) r(\lambda)$, $g_x = \int x(\lambda) g(\lambda)$, $b_x = \int x(\lambda) b(\lambda)$ respectively.

B. The linearity of the Model

The model which is obtained by combining the properties of a dichromatic color model and RGB color space is found to have linearity property. If $X(\lambda)$ and $Y(\lambda)$ are two different SPDs, the resultant colour value matrix which are combined in ratios a and b respectively is obtained by

$$C_{(aX+bY)} = aC_X + bC_Y \quad \textbf{(4)}$$

After applying the linearity property to the spectral projections we have

$$C_L = m_i c_i + m_b c_b \quad \textbf{(5)}$$

C_L is given by the linear combination of all the SPDs which contribute to the illumination of a particular surface contributing to the corresponding pixel value. The pixel values line on the surface of a plane on a parallelogram in color space (see Fig. 2). Due to the linearity property, the pixel values are confined to a two-dimensional plane rather than a three-dimensional space.

C. SEPARATION USING CHROMATICITY

In order to separate the diffuse and specular components of a single color image, the chromaticity of pixels can be used as a parameter [13]. They can be obtained using the intensity of every pixel form the corresponding RGB vectors of every pixel. The chromaticity based approach transforms the pixels in a particular color space to a two-dimensional plane which is spanned by the maximum chromaticity and intensity values of every pixel.

The chromaticity for a pixel can be defined as:

$$\beta(\boldsymbol{p}) = \frac{I(\boldsymbol{p})}{I_r(\boldsymbol{p}) + I_g(\boldsymbol{p}) + I_b(\boldsymbol{p})} \quad \textbf{(6)}$$

where $I(\boldsymbol{p})$ is the intensity of the p^{th}pixel and $I_r(\boldsymbol{p})$, $I_g(\boldsymbol{p}), I_b(\boldsymbol{p})$are its corresponding RGB values. β is a vector with R, G and B components such that $\beta = (\beta_r, \beta_g, \beta_b)$. The chromaticity factors can be separately found out for the diffusive as well as specular components using eq. (7).

In order to separate the two reflection components from a color image, its corresponding RGB color space is mapped to an intensity-maximum chromaticity space. Maximum chromaticity is a scalar which is defined by:

$$\beta_{max} = \frac{\max(I_r(\boldsymbol{p}) + I_g(\boldsymbol{p}) + I_b(\boldsymbol{p}))}{I_r(\boldsymbol{p}) + I_g(\boldsymbol{p}) + I_b(\boldsymbol{p})} \quad \textbf{(7)}$$

IV. PROPOSED METHODOLOGY

Color models specify a coordinate system of color space where each and every point in that space represents a unique color [3]. The chromaticity approach in [13] is defined in RGB color space, so in this manuscript, we extended the approach to Hue-Saturation-Value (HSV) color model to analyze whether the transformation enhances or diminishes the separation of reflection components.

A. HSV Color Model

Hue-Saturation-Value is one of the widely used color space in many image processing applications. In the HSV color model, color is represented as a combination of hue, saturation, and value which is modeled geometrically as a cone or cylinder. Hue is the color portion of the color model expressed as a number from 0 to 360 degrees. Saturation is the amount of gray in the color, from 0 to 100 percent. Value works in conjunction with saturation and describes the brightness or intensity of the color, from 0-100 percent, where 0 is completely black, and 100 is the brightest and reveals the most color. The advantage of the HSV color model is the independency of hue and value/brightness channels. Hue channel exclusively contains information about the color of pixel whereas the value channel has information regarding the intensity of the reflected light from the object. Saturation channel is found to give information about both colors as well as brightness.

B. The effect of specularity on pixels in RGB, HSV color spaces

Since DRM assumes illuminant light to be white (contains wavelength of all frequencies with uniform energy density), in RGB space for an 8-bit pixel, specularity is represented by the channel values (255,255,255). Histogram analysis (see Fig. 3) on MIT intrinsic image database [10], reveals us the fact that the presence of specularities results in a right shift of intensities in all the three channels (R, G and B).

In HSV color space specularity does not have any significant impact on the hue channel [18]. From Fig. 3, we can notice that the value of hue changes insignificantly with different levels of illumination brightness. There is a right shift in the brightness value (V) channel. In saturation channel, we find an inverse relationship between the S channel values and the specularities causing the S channel values to shift left.

Based on this observation, we propose to extend the maximum chromaticity based approach proposed in [13] to HSV color space. Removal of specularity from images is generalized as a two-step problem.

- Identifying the location of the diffuse and specular pixels from the original image which is degraded by specularity effect.
- Modifying the pixels which are corrupted by specularity.

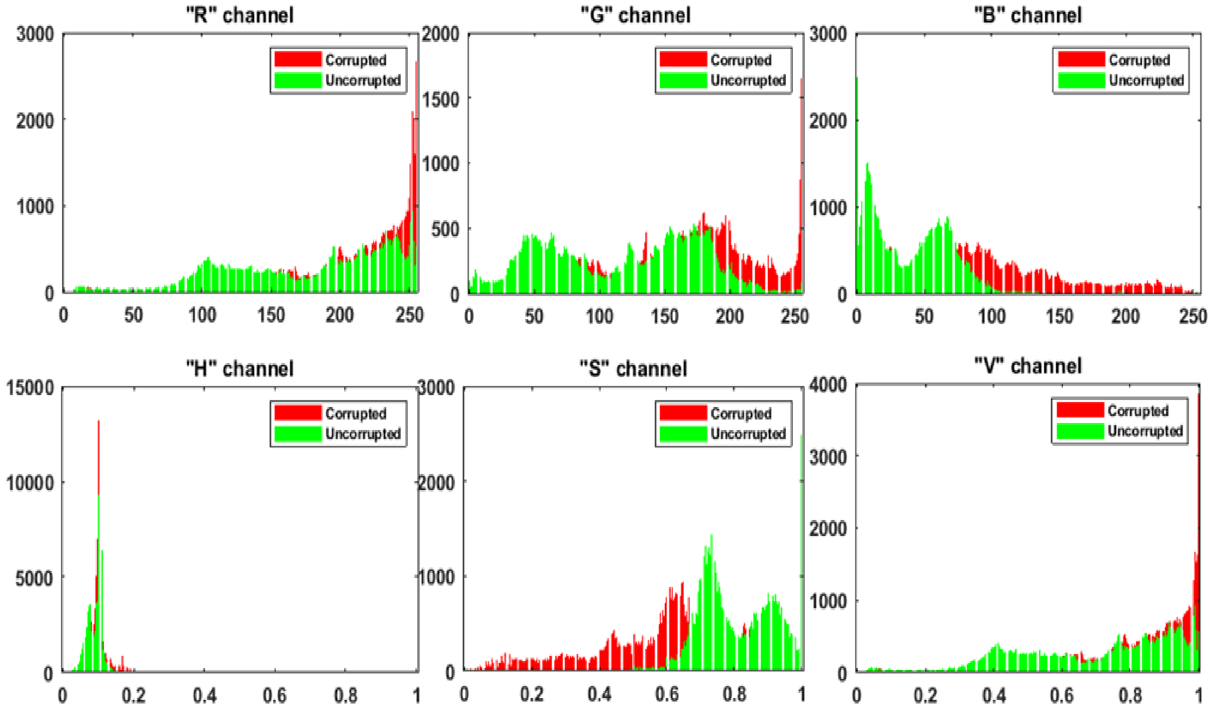

Fig. 3. Effect of specularities in RGB, HSV color spaces. In the figure, each subplot contains the histogram of corrupted and uncorrupted images taken from MIT intrinsic database [10].

The proposed extension of the maximum chromaticity based approach is given in Fig. 4.

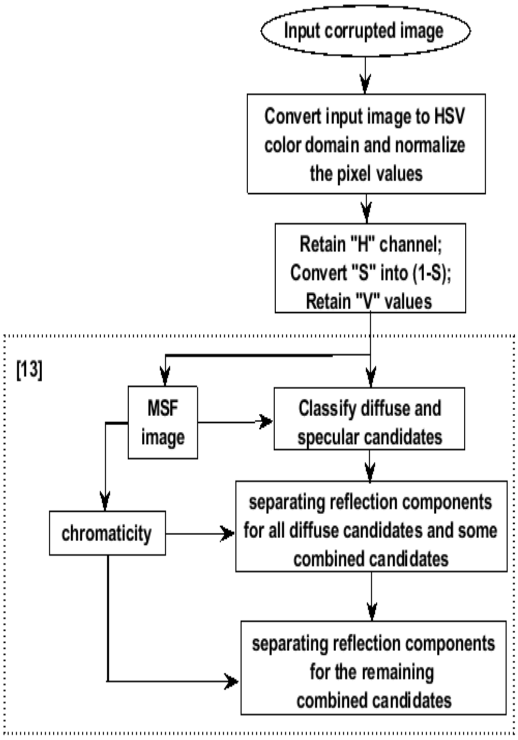

Fig. 4. Flowchart of the proposed method.

Further details of the processing details can be found at [13].

V. EXPERIMENTATION

To compare the performance of the existing and the proposed extension of [13], we have considered the single image based intrinsic image decomposition methodologies proposed in [12-17]. Real-world images from MIT intrinsic image database [10] were used for experimentation. The dataset contains 120 images of various illumination conditions captured with and without flash. The images with flash were given as the input image and the images captured under no-flash are considered as the ground truth for qualitative analysis. PSNR, SSIM, and EKI were the parameters used for comparison. Sample images of experimental output image is given in Fig. 5.

Simulation results: Visual similarity measure

For qualitative measurement of the visual similarity between the ground-truth image and the output rendered image, the authors considered four metrics, namely, Peak Signal to Noise Ratio (PSNR) [7], Structural Similarity (SSIM) index [8], Edge Keeping Index (EKI), and Time taken for the execution. Mean Square Error (MSE) represents the cumulative squared error between the reconstructed and the input image, whereas PSNR (in dB) represents a measure of the peak error. SSIM is used to quantify the amount of visual and structural information retained in the output rendered image. SSIM index measure varies between 0 and 1, where 0 corresponds to structurally completely uncorrelated images, and 1 corresponds to similar images. On the other hand, edge preservation capability and discrepancy in edge location between output and the ground-truth image is determined using EKI. EKI values vary between 0 and 1. A higher value of EKI index indicates that most of the edges in the input image are retained in the output rendered image. Experimental results are presented in Table 1.

Table. 1. Visual similarity measure values of the proposed and state-of-the-art algorithms. Database: MIT intrinsic database [10].

	PSNR (in dB)	**SSIM**	**EKI**	**Time (in Sec.)**
Shen *et al.* [12]	57.16	0.55	0.45	5.10
Shen *et al.* [13]	62.68	0.71	0.80	0.37
Shih *et al.* [14]	53.81	0.43	0.13	3.70
Li *et al.* [15]	64.40	0.78	0.73	1.09
Zhang *et al.* [16]	64.76	0.78	0.77	9.17
Li *et al.* [17]	63.45	0.75	0.81	0.41
Proposed	66.23	0.80	0.84	0.26

From the results, it is evident that the proposed approach enhances the performance of [13] and the results are slightly better than many of the compared state-of-the-art methods. The major advantage of the proposed preprocessing step of conversion into HSV color space are:

- HSV color space is less sensitive to noise.
- As Hue values do not change much because of specularity, the processing of identifying and separating reflection components is mostly confined to (1-S) and V channels only.

Due to the above-mentioned advantages, the proposed preprocessing approach provides better visual similarity measures in comparison with the existing approaches. Also, as most of the processing is confined to two channels, the proposed approach takes lesser time than [13].

B. Implementation details

All the experiments were conducted on a PC with Intel (R) Core (TM) i7 - 3770 CPU and 8:00 GB RAM. The algorithms were implemented in MATLAB R2017a without any GPU acceleration. The thresholds were tuned to attain the minimum possible localization error.

VIII. CONCLUSIONS

The specularity removal of images is a relevant but challenging task. Most of the available literature on specularity removal has been tested on synthetic images only. In this manuscript, we implemented a few state-of-the-art intrinsic image decomposition methods for single image based specularity removal application. We have extended [13] --- a chromaticity based reflection removal algorithm into HSV color domain. Experimental analysis on MIT intrinsic images [10] reveals that the proposed extension of [13] has better performance and minimum time complexity than the existing approaches.

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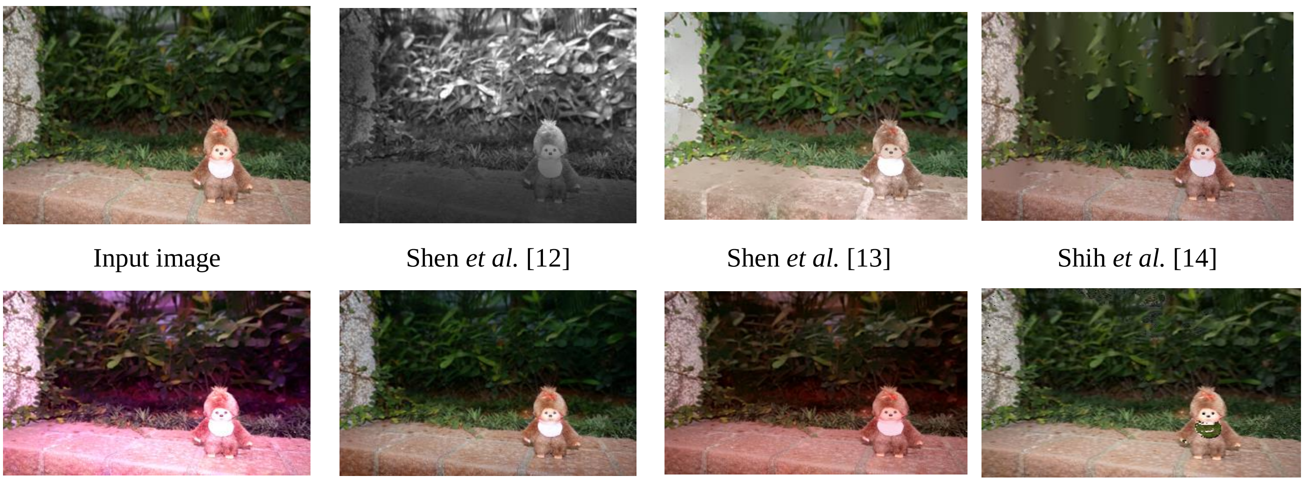

Input image | Shen *et al.* [12] | Shen *et al.* [13] | Shih *et al.* [14]

Li *et al.* [15] | Zhang *et al.* [16] | Li *et al.* [17] | **Proposed**

Fig. 5 Sample output image of the state-of-the-art algorithms [12-17] and the proposed approach.

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