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Highlights removal using reflected energy and histogram analysis

Javed Khan*, Aamir Saeed Malik*, Nidal Kamel* and Sarat Chandra Dass**

** Centre for Intelligent Signal & Image Research (CISIR), Department of Electrical & Electronics Engineering, Universiti Teknologi PETRONAS, 32610 Bandar Seri Iskandar, Perak, Malaysia*
*** Department of Fundamental & Applied Science, Universiti Teknologi PETRONAS, 32610 Bandar Seri Iskandar, Perak, Malaysia*
**Corresponding Author:*
Javed Khan, PhD candidate
Centre for Intelligent Signal & Image Research (CISIR), Department of Electrical & Electronics Engineering, Universiti Teknologi PETRONAS, 32610 Bandar Seri Iskandar, Perak , Malaysia.
Email: (javedkb84@gmail.com)

ABSTRACT

The occurrence of highlights in digital photography is an unwanted phenomenon in computer vision and image analysis. It overshadows the intrinsic color information of objects in a scene and makes computer vision algorithms to produce erroneous results. In this paper, two techniques are proposed: one for removing highlights consisting of both diffuse and specular components and the other one for removing highlights due to specular components only. The former is based on the modified Torrance-Sparrow model of specular reflection while the later technique combines Torrance-Sparrow model with local statistical analysis and recovers the color of highlights by interpolation. The results are validated on both synthesized and real images and compared with several contemporary highlights removal techniques. The comparison shows that the performance of the proposed techniques is comparable or slightly better than the previously proposed techniques.

Keywords: Specular component; diffuse component; statistical analysis; local information; image analysis.

INTRODUCTION

Image formation in digital cameras takes place by capturing light reflected from the surface of objects. Depending on the underlying mechanism, two types of reflections, diffuse and specular, can occur from the surface of inhomogeneous dialectic materials (Lin & Shum, 2001). In diffuse reflection, light infiltrates into the subsurface of an object and reflects in different directions after interacting with and refracting from pigmentation of the object. Thus, diffuse reflection represents the true color of an object. The specular reflection occurs at the interface between air and the object being observed. The occurrence of specular reflection depends on several factors such as roughness of surfaces, geometrical orientation of surface with respect to light source and viewing direction (Tominaga & Tanaka, 2003).

Due to high intensity specular reflection causes highlights in digital images. These highlights overshadow the intrinsic color information of objects being observed. In image analysis, most of the segmentation techniques have been developed with the assumption of diffuse reflection; i.e., there is no highlight in images. But, in real world, most of the materials, especially inhomogeneous dielectric objects, exhibit both diffuse and specular reflections. The image analysis algorithms treat highlights as outliers and consequently they generate erroneous results. Thus, recovering diffuse component, representing the true color of a surface, can be helpful in many computer vision algorithms.

RELATED WORK

The highlights removal techniques are based either on the physical properties of the reflected light or the statistical analysis of color spaces (Bronstein et al., 2003; Schechner et al., 2000; Artusi et al., 2011; Koirala et al., 2011). Several techniques have been developed for estimating color and spectral composition of illuminants from the specular component of reflected light (Tominaga & Wandell, 1989; Lee, 1986). Exploiting the relationship between refractive indexes of materials and specular component, techniques have been developed for categorizing the types of materials (Tominaga, 1991; Wolff, 1990). The varying polarization property of diffuse and specular components has been utilized in separating the two components by using polarization filters in front of cameras (Umeyama & Godin, 2004; Nayar et al., 1997; Kim et al., 2002).

A number of techniques have been developed for recovering diffuse component of highlights using multiple images taken from different angles (Lee & Bajcsy, 1992; Lin & Shum, 2001). The highlights regions are assumed to be non-overlapping in these images. Feris et al. (2004) proposed a method for specularity removal by solving Poisson distribution of gradient fields derived from multiple images captured under a multi-flash imaging setup. Sato & Ikeuchi (1994) analyzed a sequence of images in four-dimensional spaces to separate the two components of reflections. Similarly, a sequence of images was deployed in separating diffuse-specular component and depth recovery in Lin et al. (2002). The specularity removal techniques involving pre-segmentation are highly dependent on the segmentation results (Bajcsy et al., 1996; Klinker et al., 1988). The specular illumination detection and color rendering techniques based on several cameras or sequence of images have limited applications (Barsky & Petrou, 2003).

In recent decades, several techniques have been developed that separate specular and diffuse components based on a single image (Mallick et al., 2006; Lin et al., 2003). Tan et al. (2004) proposed a method for restoring the color of specular illumination in multi-colored images. The chromaticity (color) of specular illumination is estimated using Hough transform and histogram analysis. Furthermore, a correlation is established between illumination chromaticity and image chromaticity. The single image based technique proposed in Suo et al. (2016) performs poorly in case of the mirror-like reflection. Tan & Ikeuchi (2005) also introduced the concept of specular-free image in removing highlights from textured-surface using a single image. The highlights are successfully removed but the color of the object is significantly changed. Shen et al. (2008) proposed a method for highlight removal based on specular-free image. The specular-free image corresponding to the diffuse component is obtained by subtracting minimum component of the normalized RGB color space from each component. The pixels influenced by specular illumination are detected by thresholding the specular component obtained by subtracting specular-free image from the original color image. Finally, the diffuse component (color) of specularly illuminated pixels is recovered based on the minimum dissimilarity with any pixel in the whole image. In mirror-like specular illumination, the chromaticity of specularly illuminated pixels is similar to that of the black color or any others fulfilling the criteria R=G=B. Most of these techniques show poor performance in case of mirror-like reflection.

METHODOLOGY

According to the dichromatic model, light reflected from inhomogeneous materials consists of two components, diffuse and specular. The diffuse component, representing the color of an object, can be modeled with Lambertian's law (Nayar et al., 1989),

$$I_l = I_i \cos(\theta_i) \tag{1}$$

The irradiance of diffuse component I_l depends on the angle made by incident light with the surface normal. The intensity of specular component can be estimated with Torrance-Sparrow model (Torrance & Sparrow, 1967). The irradiance of specular component is summation of light reflected from different micro-facets making a particular angle with the surface normal. The intensity of specular component I_s is computed as below,

$$I_s = I_i exp(-\frac{\emptyset^2}{2\sigma_\emptyset^2}) \tag{2}$$

where $\emptyset$ is roughness of the surface, which indirectly indicates the randomly distributed micro-facets and $\sigma_\emptyset$ is variance of the surface roughness. Thus, reflection from inhomogeneous materials can be modeled as a linear combination of diffuse and specular components according to the dichromatic reflection model (Shafer, 1985),

$$I = \alpha I_l + \beta I_s \tag{3}$$

where α and β are mixing proportions of the two reflection components. The intensities of RGB components are related to the flux of incident light as,

$$I_c = \int_{\lambda \in \Omega} I(\lambda) h_c(\lambda) d\lambda \quad c = R, G, B \tag{4}$$

The value of a component I_c of RGB color space is obtained by integrating the product of spectral energy of incident light $I(\lambda)$ with the corresponding sensor response $h_c(\lambda)$ over the visual spectrum of light Ω. The increased spectral energy of incident light $I(\lambda)$ due to specular reflection I_s causes saturation of camera sensors. This leads to highlights in digital images. According to the dichromatic model, there are two types of reflections that can lead to highlights in digital images:

(a) The reflected light consists of both diffuse and specular components, i.e., $I = \alpha I_l + \beta I_s$

(b) The reflected light consists of the specular component only, i.e., $I = \beta I_s$

(a) Highlights removal of type I (non-saturated case)

For highlights of type I (non-saturated), a new technique is proposed. This technique is based on the modified Torrance-Sparrow model and its flow-diagram is shown in Figure 1.

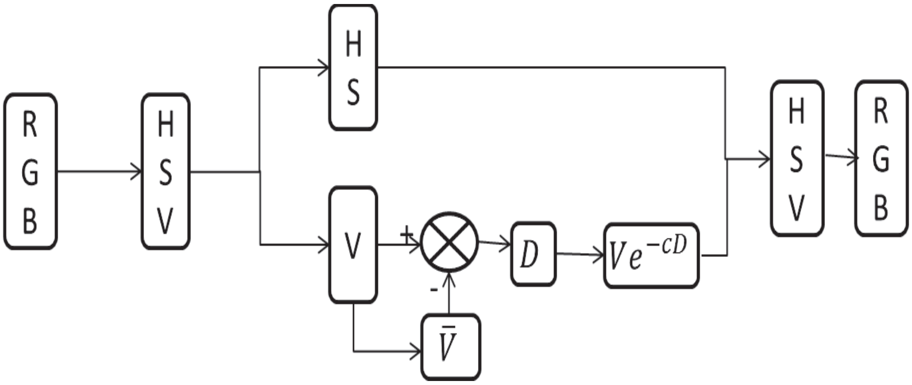


Figure 1. Flow-diagram of the proposed technique (a) for highlight removal.

First, the components of RGB color space were normalized channel-wise by 255 (8-bit). Then it was converted into HSV color space. The hue H and saturation S represent the intrinsic color information of an object, while the value (V) represents brightness information. By keeping the color components intact, the original color of the object can be preserved, while specularity is removed by modifying the brightness component according to the modified Torrance-Sparrow model. The V component of each pixel at location (*x, y*) was modified V_d according to its difference from the average value,

$$V_d(x, y) = V(x, y) \exp(-cD(x, y)) \tag{5}$$

where c is refractive index of the material and D holding the difference values of pixels from the mean value,

$$D(x, y) = V(x, y) - \bar{V} \tag{6}$$

the mean value $\bar{V}$ is calculated as below,

$$\bar{V} = \frac{1}{MN} \sum_{x=1}^{N} \sum_{y=1}^{M} V(x, y) \tag{7}$$

where N and M are the number of rows and columns, while MN is the total number of pixels in an image. The values of specularly illuminated pixels are higher than the mean value $\bar{V}$ and the values of pixels affected by shadow are lower than the mean value. The intensity profile of pixels along the strip on image in Figure 2 is shown in Figure 3.

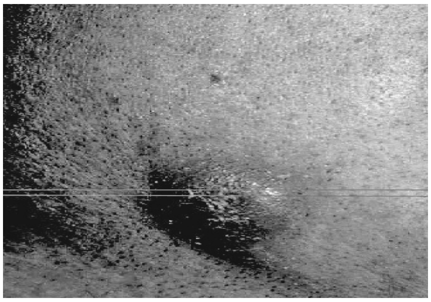


Figure 2. Selection of strip for profiling of V component.

The straight horizontal line across the intensity profile in Figure 3 represents the mean value of V component. Peaks in the intensity profile represent specularly illuminated pixels along the strip.

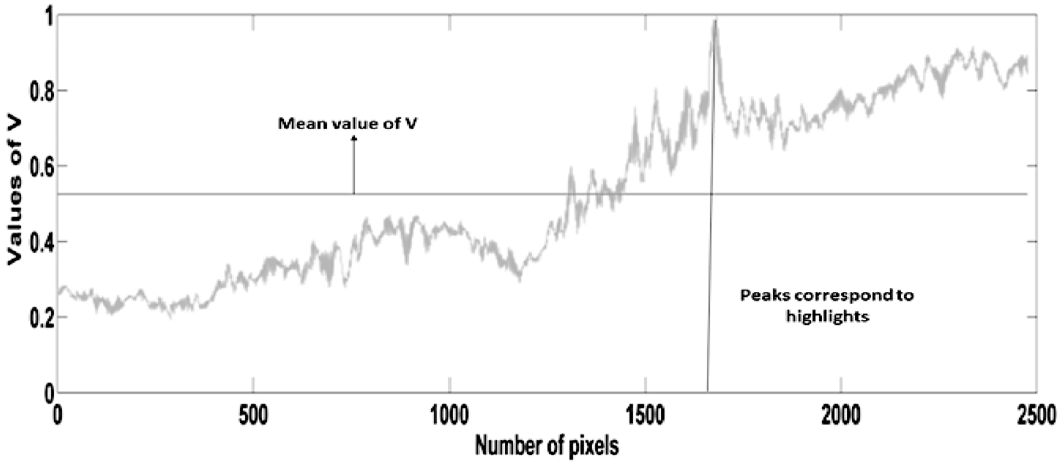


Figure 3. Profiling of pixels along the strip in Figure 2. Pixels along the strip are plotted on x-axis while V values are plotted on y-axis.

In Figure 4 the intensity profile of the same strip is shown after subtracting the mean value $\overline{V}$

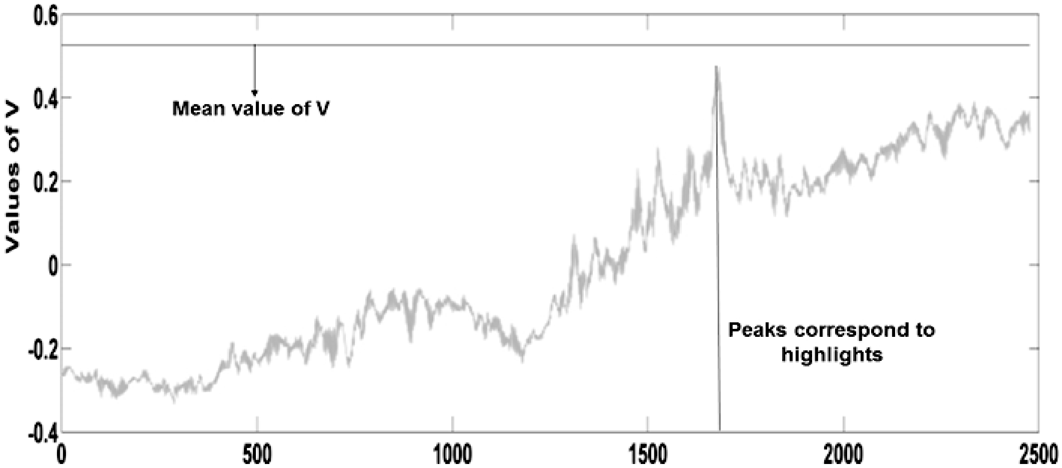


Figure 4. Profiling of V component after subtraction of mean value.
The subtraction does not change shape of the curve but contracts range of V values.

The difference value, D(*x, y*), becomes negative in case of $V < \bar{V}$ according to equation (6) while in case of $V < \bar{V}$, its values remain positive but the magnitude is decreased as shown in Figure 5.

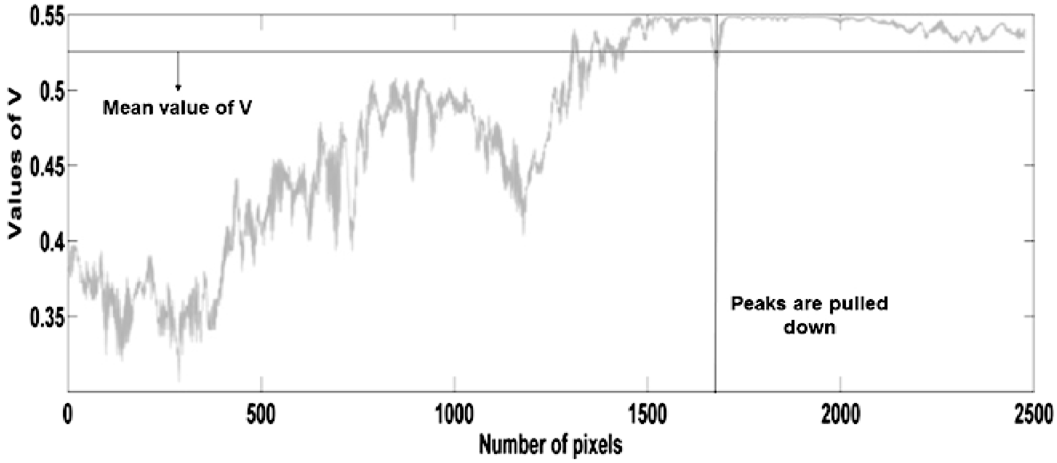


Figure 5. Profiling of V values after modification with modified Torrance-Sparrow model. Peaks values are pulled down and highlights effect is minimized.

Thus, V component of pixels in the image was modified according to its difference from the mean value $\bar{V}$. It can remove non-saturated highlights and slight shadow effects as well. In Fig. 6 (a), three main regions are encircled and labeled as A (slight shadow), B (slightly bright), and C (having highlights). In the processed image, Fig. 6 (b), the effect of the proposed technique (a) can be seen.

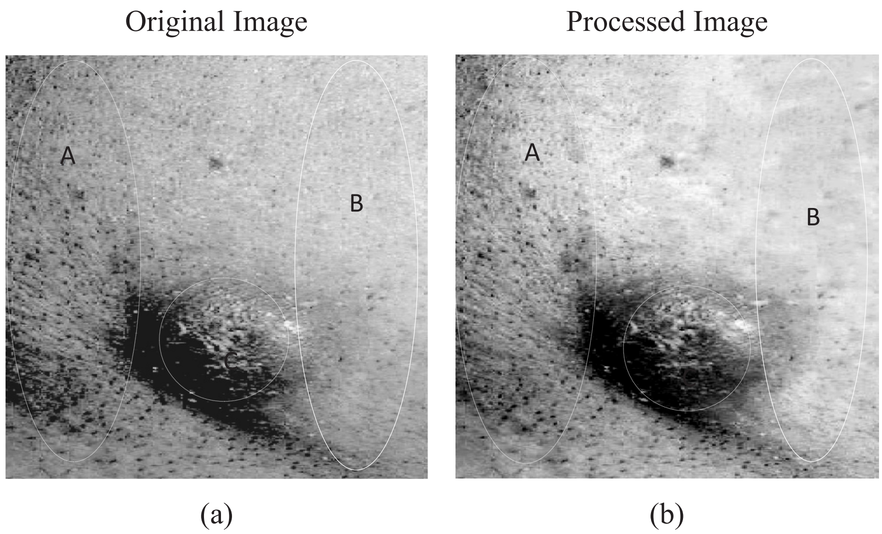


Figure 6. Removal of highlights using the proposed technique (a), (b) Highlights removal of type II (saturated case).

In mirror-like reflection (representing highlights of Type II), the color information of a body color is completely lost. Many of the recently developed methods perform poorly in recovering the diffuse component (color) in such cases. We have proposed a new technique for removing such highlights based on the closest vicinity and majority voting policy. The intensity of specular component varies depending upon the reflectivity coefficient of the surface and geometrical orientation with respect to the light source and camera. Therefore, first, the pixels influenced by specularity were fully saturated by using proposed technique (a); however, the V component was modified as follows:

$$V_d(x,y) = V(x,y)\exp\,(cD(x,y)) \tag{8}$$

Then, HSV color space was converted back into normalized RGB color space and rescaled to the range 0255-. The energy of each pixel was approximated with L1 norm as follows:

$$E(x,y) = \sum_c\ |I_c(x,y)| \tag{9}$$

where $I_c \in R, G, B$ are the three components of RGB color space. The specular pixels were detected by thresholding energy of each pixel in an image. A pixel at location (*x,y*) is specularly illuminated if $E(x,y) > T_E$ where T_E is 95% of the maximum energy (E). Once a pixel was detected as specularly illuminated, a small window of size w centered at the pixel (*x, y*) was drawn. Both diffuse and specular pixels can coexist within the window; therefore, first, non-specular pixels were obtained by applying the condition. $E(x,y) < T_E$. Then, histogram was calculated for these non-specular pixels to find the most probable candidates for color recovery of specular pixels. The most probable candidates were selected according to the bar with maximum number of elements. The diffuse component (color) of the pixel at location (*x, y*) was interpolated by averaging the corresponding values of R, G, and B components of these non-specular pixels. Flow-diagram of the proposed technique is shown in Figure 7.

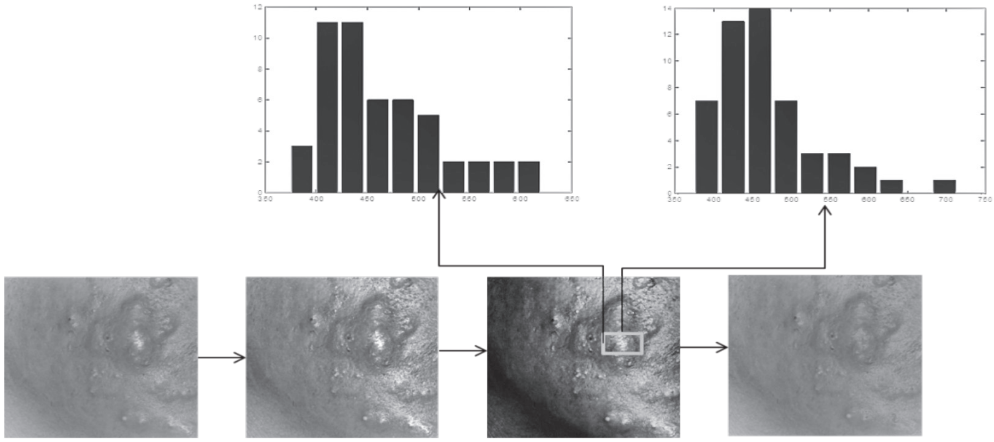
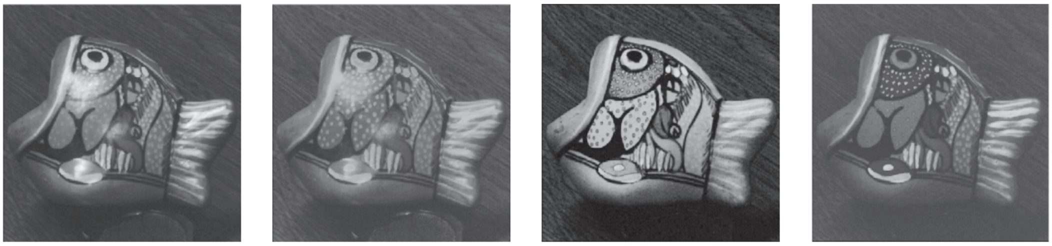


Figure 7. Flow-diagram of the proposed technique (b).

RESULTS & DISCUSSION

The proposed techniques were tested on both synthesized and real images. In Figure 8 highlights removal using different techniques is shown. In this heavily textured image of fish, the technique proposed by Shen et al. (2008) and Tan & Ikeuchi (2005) has removed highlights from the image but it can be observed that the original color has been changed in both cases. On the other hand, our proposed technique has not only removed the highlights but also preserved the original color of the objects. The results of our proposed technique (a) are comparable with those of the other techniques. However, these techniques including our proposed technique (a) do not show good performance for mirror-like reflection.



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

Figure 8. Highlights removal with different techniques (a) original image, (b) proposed technique, (c) Tan et al. technique, and (d) Shen et al. technique.

Results of the proposed technique (a) were also compared with those of Suo et al. (2016); Shen & Zheng (2013); Yang et al. (2010). In Figure 9 the original image (ground truth), original image with highlights, and results of the techniques are shown.

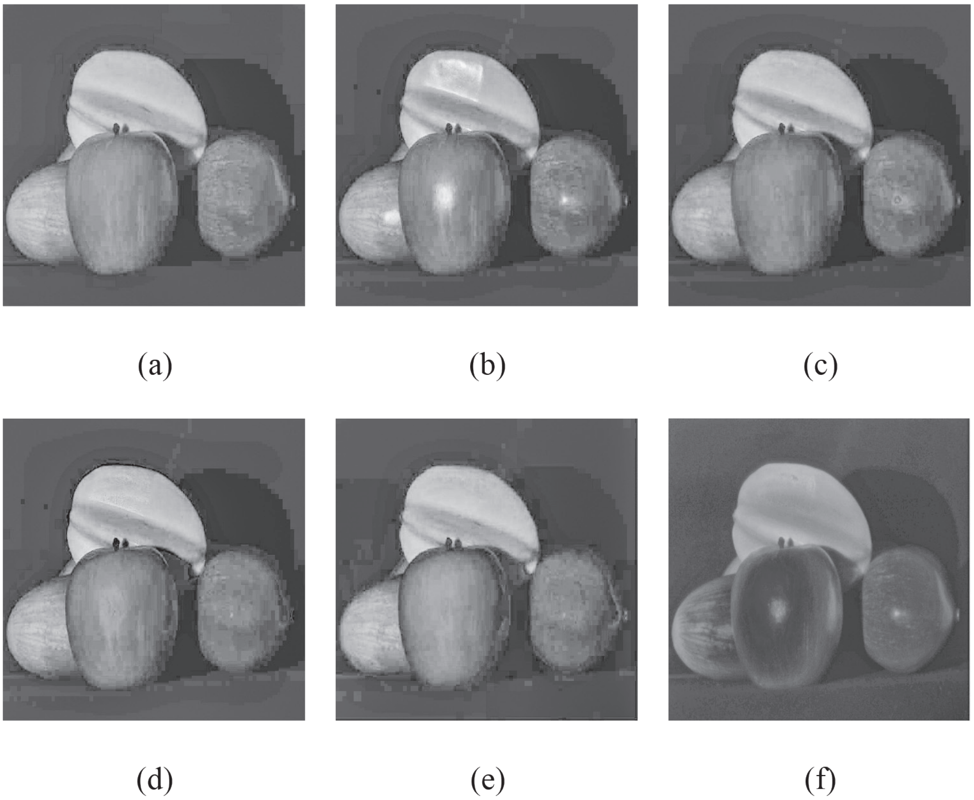


Figure 9. Comparison of proposed technique with the existing techniques.
(a) Ground truth image, (b) original image with highlights, (c) Suo et al. technique,
(d) Shen et al. technique, (e) Yang et al. technique, and (f) the proposed technique.

For quantitative comparison, peak signal to noise ratio (PSNR) values were computed and presented in Table 1. The peak signal ratio of 32.82 dB for our proposed technique (a) indicates that results are comparable with of those of Suo et al. (2016); Shen & Zheng (2013); Yang et al. (2010). The execution time of our technique is smaller than those of Yang et al. (2010) and Shen & Zheng (2013) techniques but longer than Suo et al. (2016) technique.

Table 1. Comparison of PSNR and execution time.

Techniques	PSNR (dB)	Execution time in second
Shen et al.	38.88	0.046
Yang et al.	35.74	0.097
Suo et al.	40.74	0.0085
Proposed	32.82	0.042

The results of Shen et al. (2008) technique and our proposed technique (b) for highlights removal can be seen in Figure 10. Our proposed technique estimated the diffuse component more effectively than the Shen et al. technique. In their technique, usually black color is assigned to the specular pixels. In their method, the diffuse component of specularly illuminated pixels is recovered based on the minimum distance (similarity) in the chromaticity. While finding the similarity in chromaticity, the whole image is considered. Chromaticity is computed by selecting the minimum component among R, G, and B and then subtracting it from each component. Black and other colors fulfilling the criteria R = G = B have the same chromaticity as the mirror-like specular illumination. $R = G = B \approx 255.$ Therefore, their technique performs poor in removing highlights due to mirror-like reflection.

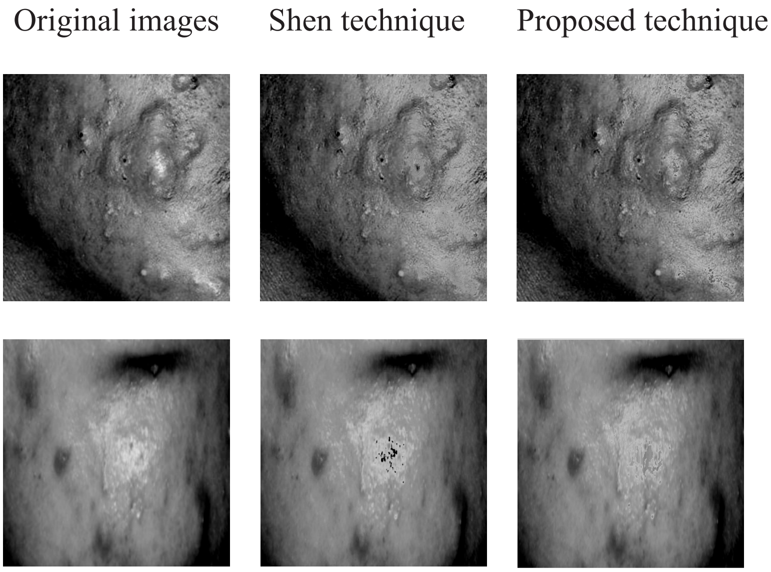


Figure 10. Comparison of highlights (saturated) removal.

As clear from the images in Figure 10, our proposed method estimated more realistic color for highlights. The mirror-like reflection is also the limiting factor of the technique proposed in Suo et al. (2016). For quantitative analysis for real scene images, coefficient of variance (COV) was computed by selecting small patches around the highlight regions in real images (Gao et al., 2017). The average COV values before and after highlights removal for our proposed technique (b) and Shen et al. (2008) are presented in Table 2. The smaller COV value of our proposed technique indicates more homogenous region after recovering the diffuse component of highlights. Thus, the proposed technique (b) recovers diffuse component of specular pixels similar to those of non-specular pixels lying in the closest vicinity.

Table 2. Comparison of COV values before and after applying highlight removal technique.

Patches	Coefficient of Variance
Original image (before)	0.0227
Shen et al. (after)	0.0142
Proposed (b) (after)	0.0058

Effect of window size on execution time

The execution time of the proposed technique (b) for different sizes of window is analyzed and shown in Figure 11. The execution time was evaluated on the image given in the running example in Figure 7. The execution time for the minimum (50) and maximum (800) size of window are 0.31 second and 0.37, respectively. The small difference (0.06) in the execution time for very large difference (750) in the window size shows that the window size has less effect on the execution time. However, execution time increases with larger highlights regions, as the window is drawn around each pixel and histogram analysis is performed.

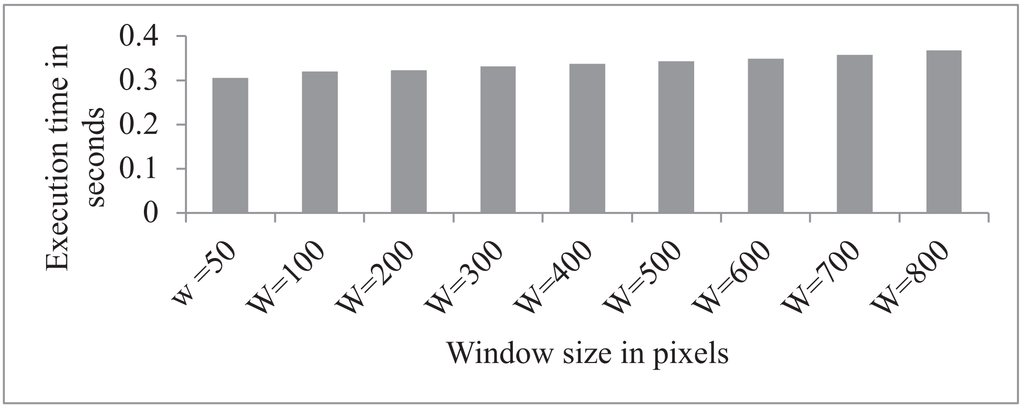


Figure 11. Effect of window size on the execution time of the proposed technique.

Application to color-based segmentation

The color recovery of highlights in digital images can be helpful in segmentation and image analysis. In Figure 12 the effect of specular illumination on color-based segmentation of acne vulgaris lesions is shown. The highlights regions in images Fig. 12 (a), (e) were treated as outliers. This demonstrates that segmentation algorithms can produce erroneous results in the presence of highlights. However, after recovering the color of highlights, the regions are segmented as lesions, as shown in Fig. 12 (c), (g). The segmentation was performed with fuzzy c-means clustering with fixed number of clusters (Khan et al., 2015). The segmentation results before and after removing highlights demonstrate that significant improvement can be achieved in the color-based segmentation by removing highlights (saturated) with the proposed technique.

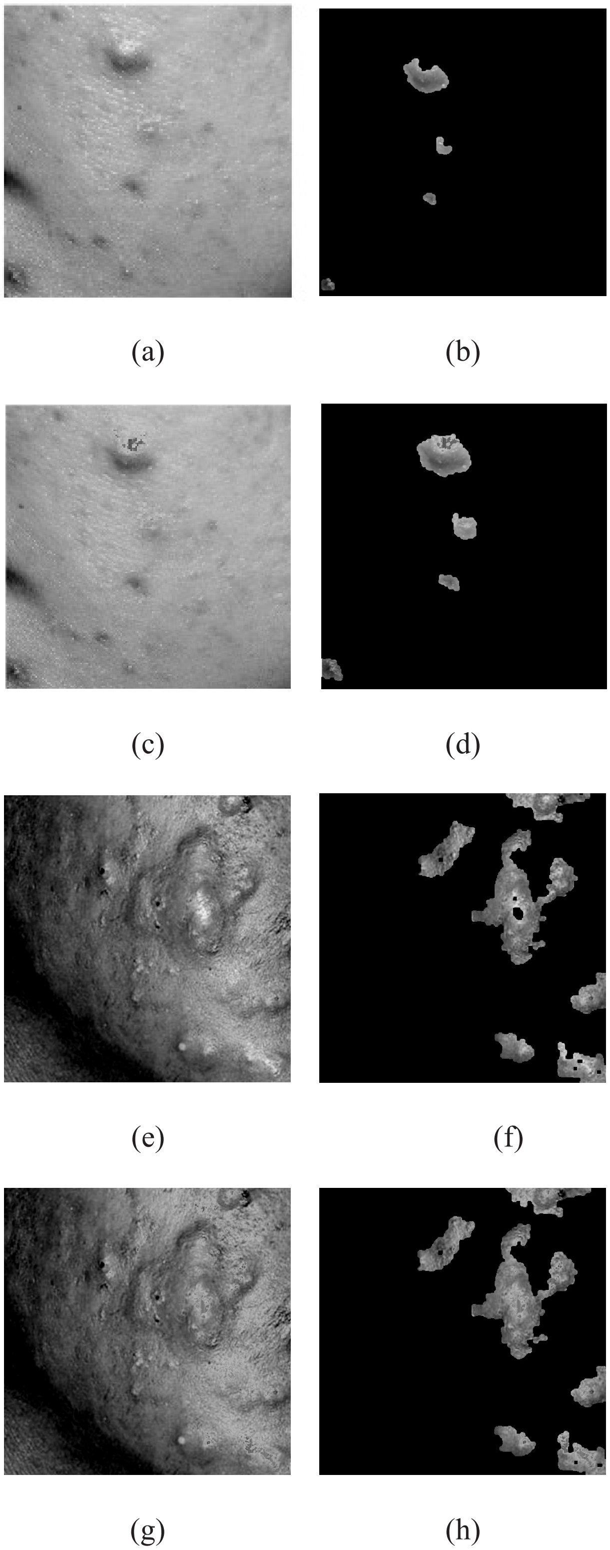


Figure 12. Effect of highlights removal on segmentation results.

The proposed technique for removing highlights, consisting of diffuse and specular components, may not show good performance in case of highlights due to mirror-like reflection. In mirror-like reflection, the color of pixels is only because of the specular component. In such cases, modifying V component of HSV color space will not recover the diffuse component of the specular pixels. On the other hand, the proposed technique (b) can produce good results in case of single-colored and multi-colored surfaces but it may not show good results in case of highly textured images. In highly textured images, changes in color are abrupt and the selection of proper window size may be difficult.

CONCLUSION

The diffuse component recovery techniques proposed in this paper are based on single image and do not require prior segmentation. Many of the diffuse component recovery techniques requiring extra equipment during imaging or multiple images capturing from different angles may be used in limited applications. The proposed technique (a) can be used for removing the highlights consisting of both diffuse and specular components, while technique (b) can be used for removing highlights due to mirror-like reflection. Substantial improvement can be achieved in color-based segmentation by removing highlights with the proposed techniques.

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إزالة الظل باستخدام الطاقة المنعكسة وتحليل الرسم البياني

جافيد خان*، عامر سعيد مالك*، نضال كامل*، سارات تشاندرا داس**

*مركز أبحاث الإشارة والصورة الذكية (CISIR)، قسم الهندسة الكهربائية والإلكترونية، جامعة بتروناس التكنولوجية

** قسم العلوم الأساسية والتطبيقية، جامعة بتروناس التكنولوجية

الخلاصة

حدوث الظل في الصورة الرقمية ظاهرة غير مرغوبة في مجال الرؤية الحاسوبية وتحليل الصورة. فتواجد الظل يغير من مكونات ألوان الصورة الأصلية وذلك يؤثر سلباً على أنظمة الرؤية الحاسوبية وذلك بإعطاء نتائج خاطئة. في هذا البحث تم اقتراح طريقتين الأولى تتمثل في إزالة الظل المتكون من المركبات المتشتتة والمنتظمة والأخرى تتمثل فقط في إزالة الظل الناتج عن المركبات المنتظمة، ويستند الأول على نموذج تورانس سبارو المعدل من الانعكاس المنتظم في حين أن التقنية الأخرى تجمع بين نموذج تورانس سبارو والتحليل الإحصائي المحلي وتسترد لون الضوء عن طريق الاستكمال. يتم التحقق من صحة النتائج على كل من الصور المخلَّقة والحقيقية ومقارنتها مع العديد من تقنيات إزالة الظل الحديثة، وتبين المقارنة أن أداء التقنيات المقترحة قابل للمقارنة أو أفضل قليلا من التقنيات المقترحة سابقاً.