Specular Detection and Removal for a Grayscale Image Based on the Markov Random Field

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Abstract. Specular detection and removal has been a hot topic in the field of computer vision. Most of the existing methods are mainly for color images, but grayscale images are widely used. For a single grayscale image with only intensity information, highlight detection and removal becomes a difficult issue. To solve this problem, the single grayscale image highlight detection and removal method based on Markov random field is presented. Each reflection component modeling is estimated by geometric relation of surface normal in diffuse and specular reflection component in the framework of Markov random field. Their maximum a posteriori estimation is calculated under Bayesian formula and highlight area is detected. Finally, image inpainting method based on the BSCB model removes highlights. Experiment reveals that this method can effectively detect grayscale image specular reflection area, improve highlight areas the repair rate.

Keywords: Computer vision · Specular detection · Markov random field

1 Introduction

An opaque object image is formed by reflecting incident light on the surface. Highlight presents the characteristics of the light source mainly, but it can be seen as the surface characteristics of the object in the visual effects. When the general image intensity values below a certain value, it belongs to the scope of diffuse, meanwhile, people's vision feel softer effect. When the reflected light is very strong, the image shows a highlight effect, and then people will have dazzling visual sense. Because of the highlight, surface texture features will weaken or even disappear, the original color of the object is obscured. Highlight results in losing partial areas information and affects the image quality, which handles computer vision image is a big distraction. It often leads to image segmentation, recognition and matching error. To be able to extract accurate object feature information and ensure that the image can be applied in image segmentation, recognition and matching, and other fields, highlights detection and removal technology is essential. Most of the existing highlight detection method is mainly for color image, rarely for the

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grayscale image, but the grayscale image is very common in the field of computer vision. For a small amount of information available, grayscale image highlight detection and removal is a difficult problem. To solve this problem, gray image specular detection and removal method based on Markov random field is presented.

2 Related Work

There are many single image highlight detection and repair methods. Current technology is more mature, more widely used method is divided into the following categories: illumination-constrained inpainting, color space conversion method, dichromatic reflection model, etc.

2.1 Illumination-Constrained Inpainting

Compared different color characteristics between specular and diffuse light, illumination-constrained inpainting [1] algorithm gives a method of interaction detection surface color highlight areas. The method is different from the traditional highlight image areas repair methods, it fully uses some useful information included highlight pixels in the guiding the repair process. General inpainting method and illumination constraints are combined through a combination of constrained complementary color process (e.g. pixel value, the illumination chromaticity analysis, light color smoothness, etc.). The algorithm ensures it can overcome the shortcomings that the general inpainting method can not remain surface subtle shading. Compared with the previous detection and removal method of a single highlight image, the algorithm can provide a better the illumination chromaticity analysis to obtain more accurate results. However, this method requires manual intervention. Because algorithm is more complex, a large amount of information is required, so it is a huge time-consuming operation and is not suitable for real-time image processing.

2.2 Color Space Conversion Method

Color space conversion method is based on the RGB color space, studying the highlight areas repair problems from another angle [2, 3]. Because each component in the RGB space not only contains the luminance information but also contains color information, and each component has a certain correlation, it increases the difficulty of repair highlight areas. If a color space can separate chrominance and luminance, then repair problem of highlight areas will become simple. Color space conversion method can achieve the desired effect, which repair highlights area well after histogram equalization for the luminance Y, but the method still exists insufficient, e.g. color space conversion method will make the image texture details lost adjusting luminance Y.

2.3 Dichromatic Reflection Model

Dichromatic reflection model describes essentially [4–6] two reflection processes, specular reflection Component and diffuse reflection Component. When the object surface is relatively smooth, specular reflection Component is stronger than the diffuse reflection Component; on the contrary, the surface is rough, diffuse reflection Component is stronger than the specular reflection Component. There is a link between surface structure and spectrum of the incident light. If the surface structure is smooth, spectral structure does not change, and the color will not change; on the contrary, because the rough surface will lead to changing the spectrum structure, so the color will change. On the basis of the dichromatic reflection model, the each pixel color of object is regarded as a linear combination between the specular reflection component and the diffuse reflection component.

Klinker et al. [7] proposed a single image highlights detection and removal algorithm according to Shafer's dichromatic reflection model [8]. Klinker found a T-shaped formed from distribution diffuse pixels and highlight pixel in the RGB color space. Principal component analysis was used to fitting diffuse and light color vector in the diffuse reflection area and highlight regions. Specular reflection component was removed quickly by the use of these two vectors for projection. However, the highlight pixel clusters usually is distorted because of the surface roughness, geometry [9] et al. Therefore, principal component analysis to estimate the light source colors is usually inaccurate, which largely reduces the versatility of the method.

Although the above methods are able to achieve a good effect of highlight detection and removal, these methods analysis mainly for color image. It can not be applied to grayscale image highlight detection and recovery. The single grayscale image highlight detection and removal method based on Markov random field is presented.

3 Reflection Model

On the basis of the dichromatic reflection model, because normal direction of the diffuse light points is inconsistent and the normal direction of the specular reflection light is unchanged, using the geometric relationship between the diffuse and specular surface normal vector locates the highlight area. Relationships between geometric constraints are shown as Fig. 1, The dichromatic reflection model is given as follow:

$$I = m_d(\vec{n}, \vec{s}, \vec{v}) \int_\lambda f(\lambda)e(\lambda)c_d(\lambda)d\lambda + m_s(\vec{n}, \vec{s}, \vec{v}) \int_\lambda f(\lambda)e(\lambda)c_s(\lambda)d\lambda. \tag{1}$$

Here $m_d(\vec{n}, \vec{s}, \vec{v})$ and $m_s(\vec{n}, \vec{s}, \vec{v})$ represents the weight function of diffuse and specular reflection respectively; $\vec{n}$ is the surface direction, $\vec{s}$ is direction of the light source, $\vec{v}$ is direction of the view; $f(\lambda)$ represents sensor transfer function for the three primary colors; $e(\lambda)$ represents the incident spectral energy distribution function; $c_d(\lambda)$ is diffuse reflectance; $c_s(\lambda)$ is specular reflectance.

Specular reflection is reflected parallelly by the bundle of parallel incident light from the surface to a certain direction, mainly reflecting the characteristics of the source. As shown in Fig. 1, specular reflection of the incident light (i.e. light source), surface normal vector and the reflected light (viewing direction) is in the

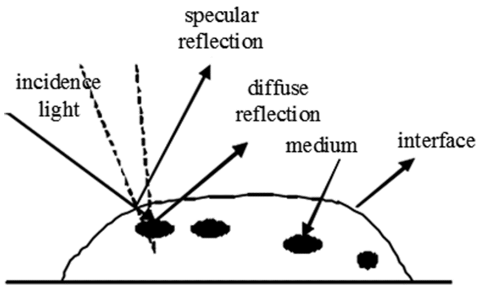


Fig. 1. Geometry of specular reflectance.

same plane, its incidence angle (the angle $\vec{s}$ between $\vec{n}_s$) and the reflection angle (the angle $\vec{v}$ between $\vec{n}_s$) is equal. According to the general definition, specular surface normal vector can be expressed in the form of Formula 1.

$$\vec{n}_s = \frac{\vec{s} + \vec{v}}{\|\vec{s} + \vec{v}\|}. \tag{2}$$

Specular reflection model is defined by the Beckmann distribution as follows:

$$P_s(i,j) = \frac{1}{\sqrt{2\pi\sigma_s}} \exp\left[-\frac{1}{2}\left(\frac{\theta}{\sigma_s}\right)^2\right]. \tag{3}$$

$P_s(i,j)$ is specular reflection distribution, σ_s is the variance of the angular distribution parameter control.

Diffuse reflection is projected by parallel incident light to opaque objects, due to the normal direction of each point is inconsistent, resulting in the phenomenon of reflection light reflected irregularly in all directions. Diffuse reflection light reflecting surface features of the object is shown as Fig. 1. According to Lambert's law, the intensity value of the point (i,j) is usually given by the formula:

$$I(i,j) = \vec{n}_{i,j} \cdot \vec{v}_{i,j}. \tag{4}$$

where $I(i,j)$ is the surface normal vector of the pixel (i,j).

We assume that the observed specular intensities follow a Gaussian distribution. Under these assumptions we can write

$$P_d(i,j) = \frac{1}{\sqrt{2\pi\sigma_d}} \exp\left[-\frac{1}{2}\left(\frac{I(i,j) - \vec{n}_{i,j} \cdot \vec{v}_{i,j}}{\sigma_d}\right)^2\right]. \tag{5}$$

Where $P_d(i,j)$ is the diffuse distribution with variance σ_d^2, the mean value is defined by $\vec{n}_{i,j} \cdot \vec{v}_{i,j}$.

For a given single grayscale highlight image I, maximum posterior probability is estimated by Bayes formula:

$$(P_d(i,j), P_s(i,j)) = \underset{p_d, p_s}{\operatorname{argmax}}\, I(I_d, I_s|I). \tag{6}$$

Bayesian criterion:

$$P(I_d, I_s|I) \propto P(I|I_d, I_s)P(I_d|I_s)P(I_s) \tag{7}$$

Since the original image without highlight and the specular reflection component are uncorrelated, Eq. (7) can be simplified to:

$$P(I_d, I_s|I) \propto P(I|I_d, I_s)P(I_d)P(I_s) \tag{8}$$

where $P(I|I_d, I_s)$ is the likelihood function, showing before and after the restoration error obedience distribution, $P(I_d)$ and $P(I_s)$, respectively, represent a priori of I_d and I_s).

We assume that likelihood function $P(I|I_d, I_s)$ follow a Gaussian distribution. Under these assumptions we can write

$$P(I|I_d, I_s) = \prod_{i,j} \exp(-|I(i,j) - I_d(i,j) - I_s(i,j)|^2) \tag{9}$$

In Fig. 2 we provide some more detailed analysis of the specular reflection model and diffuse reflection model. Figure 2a shows three pixels: a (a diffuse pixel), b (a specular pixel located between pixels a and c), and c (the highlight's brightest pixel).

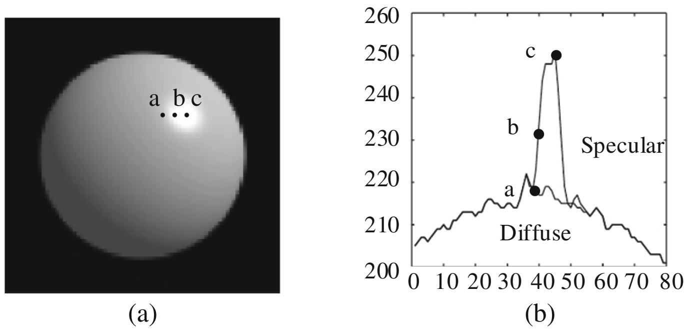


Fig. 2. (a) Original image. (b) Specular reflection model and diffuse reflection model.

4 Image Inpainting Method Based on the BSCB Model

Image inpainting of highlight areas can be seen as the original image the recovering process. Most inpainting methods analyze color pictures, so it can not be applied in a single grayscale image. BSCB model is presented by Bertalmio, Sapiro, Caselles and Ballester according to actual image patching process of manual repairing artists, and it is an image inpainting method established based on partial differential equations. Its main idea is based on the manual repair experience, edge information diffusion into the area to be repaired along the isolux line direction, shown in Fig. 3.

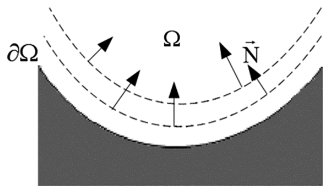


Fig. 3. BSCB model repair process of information diffusion.

We suppose $I_0(i,j)$ is the original highlight grayscale image with size m × n, and establish a set of image sequences $I(i,j,n)$, here $I(i,j,0) \to I_0(i,j)$, and $\lim_{n \to \infty} I(i,j,n) = I_R(i,j)$, in which $I_R(i,j)$ is the final result of repair.

BSCB model patching process as following two steps:

(1) mathematical model of BSCB repair process can be written as follows:

$$\text{for } I^{n+1}(i,j) = I^n(i,j) + \Delta t I_t^n(i,j) \text{ any } (i,j) \in \Omega. \tag{10}$$

where n represents iteration times, (i,j) is the pixel coordinates point of the grayscale image, Δt represents iterative step, $I_t^n(i,j)$ is image $I^n(i,j)$ without highlight, Ω represents highlight areas, patching process only removes highlight areas.

(2) highlight areas on the boundary isolux line diffuse into highlight areas, as following:

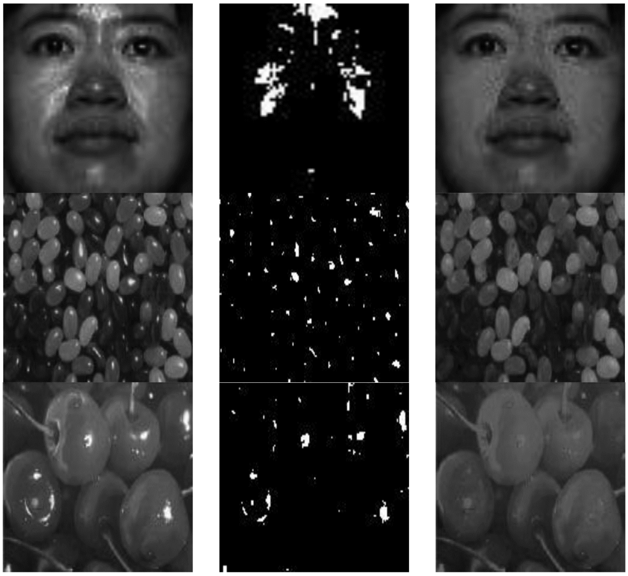
$$\frac{\partial I}{\partial t}(x,y,t) = g_\varepsilon(x,y)k(x,y,t)|\nabla I(x,y,t)|, \quad (x,y) \in \Omega^\varepsilon. \tag{11}$$

where $g_\varepsilon(x,y) = \begin{cases} 0 & (x,y) \in \partial\Omega; \\ 1 & (x,y) \in \Omega. \end{cases}$ $g_\varepsilon(x,y)$ is a smooth function on the Ω^ε. Ω^ε is a circle with a radius of ε. $k(x,y,t)$ is Euclidian curvature of isolux line.

Steps (1) and (2) are repeated until the output image sequence $I^n(i,j)$ without significant changes, i.e. $I^{n+1}(i,j) \approx I^n(i,j)$. The iteration stops, then highlight removal process is complete.

5 Experimental Result

Figure 4a, b, and c shows the result of highlight detection and removal. Figure 5a shows the images in highlight areas relatively steep. However, Fig. 5b is smoother than the Fig. 5a. In order to further quantify the comparison, to verify the validity of this method, as shown in Fig. 6. Figure 6a and b show, respectively, original image of Fig. 3a the first row and image after highlight removal. Compared with Fig. 6a, higher luminance values reduce and luminance value distribution remained largely unchanged in the Fig. 6b. Experiment reveals that the method is better in processing details; it is able to effectively detect small specular reflection area hidden in grayscale images, and only remove the highlight region, so it does not affect the other areas of the image information, retaining the original image information in the maximal degree. Compared with the traditional algorithms, the method is better to prevent image distortion.



(a) (b) (c)

Fig. 4. (a) Original image. (b) Specular image. (c) Image removed specular

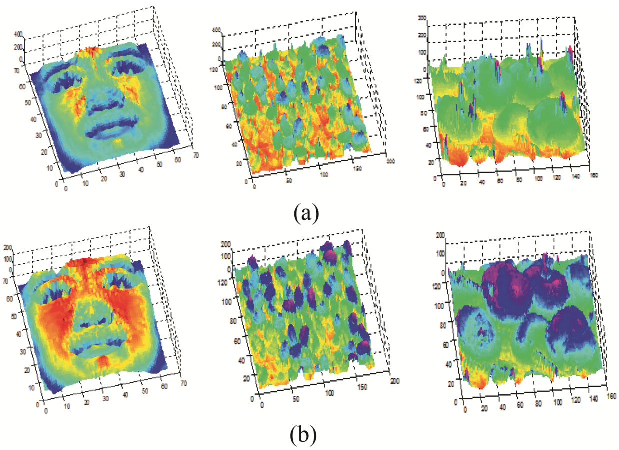
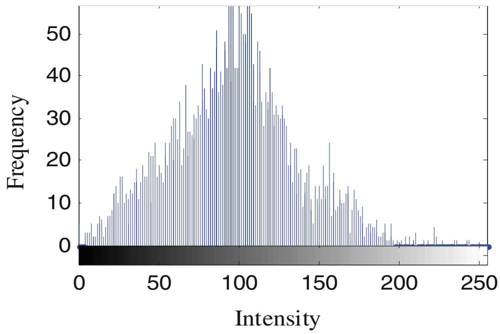
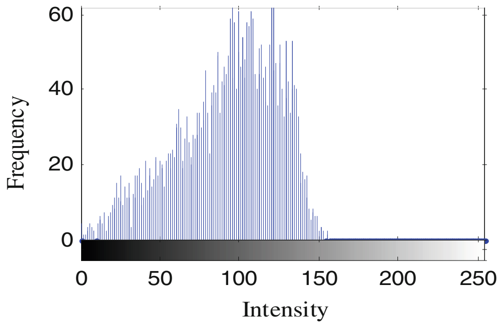


Fig. 5. (a) Original three-dimensional diagram. (b) Three-dimensional diagram after removed the highlight



(a)



(b)

Fig. 6. (a) Original image of Fig. 4a the first row. (b) Image after highlight removal.

6 Conclusion

Most of the existing methods are mainly for color images, but grayscale images are widely used. For a single grayscale image with only intensity information, specular detection and removal has been is the difficulty of computer vision. So, the single grayscale image highlight detection and removal method based on Markov random field is provided. Firstly, the diffuse and specular reflection components is modeled. Secondly, their maximum a posteriori estimation is calculated under Bayesian formula, and then highlight area is detected. Finally, highlight areas are recovered by image inpainting method based on the BSCB model. Experimental results show that the proposed algorithm only remove the highlight region, so it does not affect the other areas of the image information, and it is better to prevent image distortion, improves the accuracy of surface recovery for highlights image.

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