Shadow Detection and Removal from Solo Natural Image Based on Retinex Theory

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Abstract. Shadows are physical phenomena observed in most natural scenes. They can cause many problems in computer vision performance. The paper addresses the problem of shadow detection and removal from solo image of natural scenes. Our method is based on Retinex theory which is an image enhancement and illumination compensation model of the lightness and color perception of human vision. The approach proposed here does not use any special prior knowledge and assumptions. The shadow extraction algorithm originates from a simple idea that the human-vision-based Retinex has the natural ability to enhance the shadow region of an image no matter it is penumbrae or umbrae. The penumbrae and umbrae regions will be highlighted if we compare the Retinex-enhanced images with original images. Then through adding smooth light forcibly to shadow edges and introducing shadow edge masks, we reduce the effects of shadow edges in the Retinex enhancement processing. Experiment results validate the approach.

Keywords: Shadow detection; Shadow removal; Retinex Theory; Machine Vision.

1 Introduction

A shadow occurs when an object partially or totally occludes direct light from a source of illumination. Shadows are one of the principal factors affecting computer vision performance in outdoor scenes [1]. In image segmentation, the shadow boundaries may be confused with real object boundaries. In motion estimation, the computation of optical flow is susceptible to illumination changes caused by shadows. In supervision, for the influence of shadow, erroneous target may be tracked [2]. Identifying and removing shadows in image is of great practical significance in image segmentation, and object tracking and supervision, etc.

Yet the problem of shadow detection and removal, especial for solo uncalibrated natural image, is a difficult problem. Shadow detection algorithms can be classified as property-based and model-based algorithms. Model-based techniques rely on models representing the a priori knowledge of the geometry of the scene, the objects, and the illumination. Property-based techniques identify shadows by using features such as geometry, brightness or color of shadows. Model-based approaches suits to particular

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situations, while it shows less robustness than property-based algorithms when the scene and illumination conditions change [3].

In [4], the author exploits some statistical properties of the shadow borders after they have been enhanced through a simple edge gradient based operation using a challenging outdoor traffic scene as a "training" sequence. Cucchiara [5] considered the color independence property in the HSV color space to detect shadow. A. Leone, C. Distante [6] presented shadow detection of moving objects in visual surveillance environment by evaluating the similarity between little textured patches, since shadow regions present same textural characteristics in each frame and in the corresponding adaptive background model. Nicolas Martel-Brisson [7], used the Gaussian mixture model (GMM) learning ability to build statistical models describing moving cast shadows on surfaces. Jean-Marie Pinel and Henri Nicolas [8] based on the estimation of the 2D position of the light source to analyze the shadows in natural video sequences. The methods mentioned above detected and removed the shadows by using the sufficient information in image sequences. These methods are difficult to be applied to single outdoor image.

T Gevers and H.M.G. Stokman [9] proposed a taxonomy of color invariant edges. The edge classifier is derived labeling color transitions into shadow, geometry or shading edges, highlight edges, and material edges. Michael Nielsen and Claus B Madsen [10] introduced a new concept within shadow segmentation for usage in shadow removal and augmentation through construction of an alpha overlay shadow model. More recently, Graham D. Finlayson, et al. [11][12]made a great step in removing cast shadows from single images. They set out in [11] to derive a 1-d illumination invariant shadow-free image, using the invariant image together with the original image to locate shadow edges. The method can remove shading in umbra regions lit by the Planckian light, but not work in penumbra region.

In this paper, we proposed a method to detect and remove both penumbrae and umbrae from solo image based on Retinex theory. This paper is organized as follows, in section 2 the basis of Retinex theory and Kimmel Retinex algorithm are presented. In section 3 and section 4 introduce our method of shadow extraction and shadow removal separately, followed by experimental results are shown and discussed in section 5. And finally, in section 6 general conclusions of this work are presented.

2 Retinex and the Variational Framework

2.1 Retinex Theory

The primary goal of the Retinex proposed by Land is to decompose a given image I into two different images, the reflectance image R and the illumination image L, such that, at each point (x, y) in the image domain,

$$\mathrm{S}(x, y) = R(x, y) \cdot L(x, y) \tag{1}$$

The conversion to the logarithmic domain by $s = \log(S)$, $l = \log(L)$, $r = \log(R)$, and thereby $s = l + r$. Since the illumination images represent the distribution of the lighting and shading, separating it from reflectance is useful to cancel out the effect of shadows. Land's theory could only remove the penumbrae in image since they were based on the following assumptions [12]:

a. Mondrian world model.
b. Spatially smooth illumination.
c. Lambertian surfaces.

Lambertian surfaces assumption is forcing that there is no specular reflectance in image. The Mondrian world and smooth illumination assumptions assume that there is a generally clear signal at each of the boundaries between objects whereas there are no sharp boundaries between shadows and the background.

2.2 The Variational Framework

Since the proposal of the Retinex theory, J. McCann, D. J. Jobson, et al. proposed and improved different Retinex algorithms from different angles [13][14]. In 2001, Ron Kimmel [15] proposed a variational model for the Retinex theory.

Its variational framework proposed by Ron Kimmel [15] is described as follows:

$$\begin{aligned} &\inf F[l] = \inf\left(\int_{\Omega} \left(|\nabla l|^2 + \alpha(l-s)^2 + \beta|\nabla(l-s)|^2\right)dxdy\right) \\ &\text{Subject to} \quad l \geq s, \text{and} < \nabla l, \vec{n} >= 0 \ \ on\ \partial\Omega \end{aligned} \tag{2}$$

where Ω is the support of the image, $\partial\Omega$ is boundary, and $\vec{n}$ is the normal to the boundary, and α and β are free non-negative real parameters. In the functional $F[l]$, the first penalty term $(|\nabla l|^2)$ forces spatial smoothness on the illumination images. The second penalty term $(l-s)^2$ forces proximity between l and s. The third term forces the reflectance image to be spatially smooth.

3 Shadow Detection Based on Retinex Theory

The Retinex is an image enhancement algorithm that provides a high level of dynamic range compression and color constancy. Moreover, it can be applied to arbitrary images without any prior knowledge of camera calibration. As a result, it has become a popular tool in image preprocessing.

Retinex theory mainly aims to correct uneven illumination. It has strong correcting effect on penumbrae but weak effect on umbrae. Because of the shortcoming inheriting in Retinex theory mentioned above it is limited in practical applications. One solution is to mark the umbrae regions and then remove them by other methods. Yet it brings another problem of differentiating penumbrae from umbrae since they have many similar features except that umbrae's edges are sharper then those of penumbrae. There are no clear dividing lines between them. It is hard to judge Retinex enhancement algorithm could deal with how vague the shadows are. And it is also difficult to tell how sharp the shadow should be in order to get good results for other umbrae-shadow-remove methods [11][12] for the same reason. So handling the two types of shadows by a same method will be a better solution. We present a method to extract penumbrae and umbrae from solo natural image based on Kimmel Retinex Algorithm.

Penumbrae regions do not have strong edges; the illumination correction by Kimmel Retinex Algorithm can extend to the edge of the penumbrae edge. So the different between the output image and the original image will pop out the whole penumbrae region. For umbrae regions show relative sharp edges, it is hard for Kimmel Retinex Algorithm to span the edges part of umbrae regions, so it fails to correct the umbrae region. Yet, because Kimmel Retinex Algorithm only compare the surround pixels with the center ones, the center of the umbrae region will be strongly brightened for the center retains the properties of shadows which are familiar with those of penumbrae regions, as shown in fig 1.

Fig. 1. The left image is the original image; the right the enhanced image by Kimmel Retinex Algorithm, inside the ellipse regions of which is strongly illuminated at the center though not brightened correctly at the boundaries

Our approach is based on the comparison of the image enhanced by Kimmel Retinex Algorithm with the original image. A proposed algorithm mainly involves the following steps:

(1) To enhance the original image by Kimmel Retinex Algorithm. In order to reduce the calculating complication, we map the input intensity $\mathrm{S}_I = \sum_i S_i$ (in the case of three-channels $S_I = S_{red} + S_{green} + S_{blue}$) to the output intensity R_I using formula(2) [16].

(2) To get the difference map $Diff_I$. $Diff_I$ is got by subtracting the original input intensity from the extracted image R_I, that is, $Diff_I = R_I - \mathrm{S}_I$. The shadow regions in $Diff_I$ are highlighted. After deriving threshold T, we could do the following clipping operation to obtain a binary vague shadow mask for further process:

$$PS(x,y) = \begin{cases} 1 & \text{if } Diff_I(x,y) > T \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

The $PS(x,y)$ is the binary possible shadows mask.

(3) To extend PS to the boundaries of the possible shadows. Since Kimmel Retinex Algorithm enhances the center of umbra regions, PS image may not include the whole shadow regions. Here, we use traditional region growing image segmentation method. The image enhancement algorithm may bring some noises to the output

image, so the binary morphological erosion algorithm is applied to eliminate small points before the extension.

(4) To further confirm the shadow regions. The shadow regions sheltered from direct sunlight are of lower brightness, while they are of higher saturation because the earth's atmosphere scatters a certain number of short-wave blue rays of sunlight, as shown in fig 2. [10].

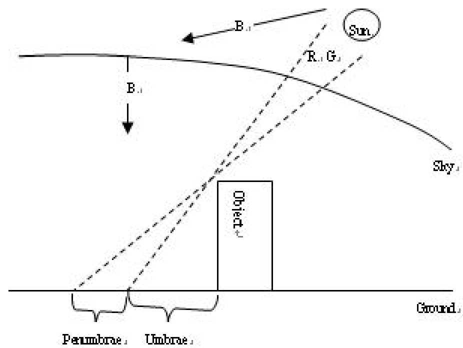


Fig. 2. Shadow model where the umbrae region is lighted mainly by short-wave blue rays of sunlight, and the penumbra is partly by red and green rays and more blue rays

HSI color space is applied here in order to get the saturation S_{sat} and the brightness S_b of the original image. We use S_{sat} and S_b to justify the shadow regions gotten in step (3).

We set that: If $(\mathrm{S}_{\mathrm{sat}}(x, y) - S_b(x, y)) / (\mathrm{S}_{\mathrm{sat}}(x, y) + S_b(x, y)) < T$, then pixel (x, y) is not in shadow regions, otherwise it is. The result is as follows,

(a) (b) (c)

Fig. 3. Shadow extraction result. (a) is the original image; (b) output image of step(3); (c) output image of step(4).

4 Shadow Removal Based on Kimmel Retinex Algorithm

Kimmel Retinex algorithm contains a defect of dealing with shadow regions. Kimmel suggest that because illumination typically changes more gradually than does surface reflectance, the effect of a changing illumination could be removed by forces spatial smoothness on the illumination images. When there is umbrae in the original image, though the illumination inside of umbrae and non-umbrae regions changing smooth, it changes sharply near the boundaries of umbrae. The illumination in such images is piecewise smooth. But the reconstruct illumination images gotten by Kimmel Retinex algorithm are smoothed globally which suffer from artificial halos because the Kimmel Retinex algorithm fail to reconstruct piecewise constant illumination. It is why the boundaries become wider and darker in the output image processed by Kimmel Retinex algorithm.

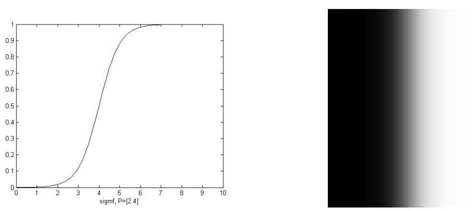
Looking from the angle of formula (2), the first penalty term $(|\nabla l|^2)$ forces spatial smoothness on the illumination images. $|\nabla l|^2$ is the primary factor in determining the evaluating results of illumination in Kimmel Retinex algorithm. However, $|\nabla l|^2$ is high near the boundaries between the umbrae and non-umbrae regions which further deviates from the real pixel values. So the pixels inside and outside shadow regions should be considered separately.

Choosing the shadow regions as example, the method presented here is of two steps. Firstly we add an artificial illumination on the outside of the boundaries Ω_b to reduce the sharpness of shadow boundaries. Here we utilize Sigma to synthesize the illumination as shown in the following:

Equation (4) is a standard sigmoid function,

$$s(t) = \frac{1}{1+e^{-t*k}} \tag{4}$$

where K=1/3 and controls the steepness of the S curve. $s(t) \in [0,1]$ within $t \in [-10,10]$.



(a) (b)

Fig. 4. (a)Sigma models; (b) Sigma synthetic image

Here, we add an artificial Sigma illumination on the outside of the boundaries Ω_b as follows:

$$S'(x,y) = \begin{cases} S(x,y) & (\mathrm{x},\mathrm{y}) \notin \Omega_{\mathrm{outside}} \\ S(x,y) * s(t) & \text{其中，} \ \mathrm{t} = \min(\sqrt{(\mathrm{x}-\mathrm{x}')^2 + (y-y')^2}), \\ & (\mathrm{x},\mathrm{y}) \in \Omega_{\mathrm{outside}}, (\mathrm{x}',\mathrm{y}') \in \Omega_{\mathrm{d}} \end{cases} \tag{5}$$

Also, in this framework, we assume that all the pixels along the shadow boundary and the regions we add artificial illumination have the same reflectance on both sides. The method proceeds as follows: we reduce the effects by $T\left(|\nabla l|^2\right)$, that is, the derivatives of l are decided by function $T\left(|\nabla l|^2\right)$:

According to a function T(▽I) such that,

$$T(|\nabla l|^2)=\begin{cases}0, & |\nabla l|^2\in\Omega_{\mathrm{d}}\ or\ |\nabla l|^2\in\Omega_{outside}\\ |\nabla l|^2 & \text{otherwise}\end{cases}\tag{6}$$

Summarizing Formula (4),(5)and (6), the improved Kimmel Retinex algorithm can be described as follows,

$$\begin{gathered}\inf F[l]=\inf\left(\int_{\Omega}\mathrm{T}(|\nabla l|^2+\alpha(l-s')^2+\beta|\nabla(l-s')|^2)dxdy\right)\\ \text{Subject to}\quad l\geq i,\text{and}<\nabla l,\vec{n}>=0\ \ on\ \partial\Omega,\quad where\quad \mathrm{s'=log(S*s(t))}\end{gathered}\tag{7}$$

Then we deal with the non-shadow regions in the similar way. Combining the two output parts of the image, we can get the illumination constant image without shadows. Experimental results are given in section 5.

5 Experimental Results

In this section, five groups of results are demonstrated include umbra and penumbra regions. Each group is displayed by one line.

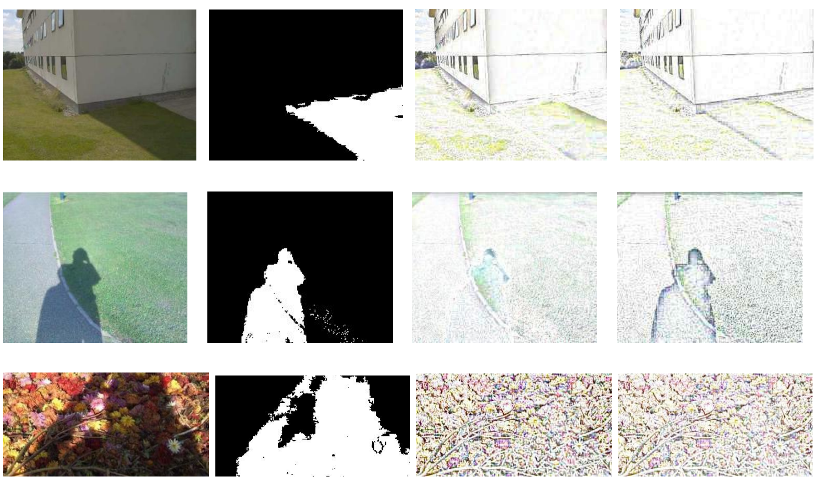


Fig. 5. Experimental results. The first column is the original image; the second column is the extracted shadow regions; the third column is the output image with shadow removed; the last column is the output image only dealt with Kimmel Retinex algorithm as the comparisons.

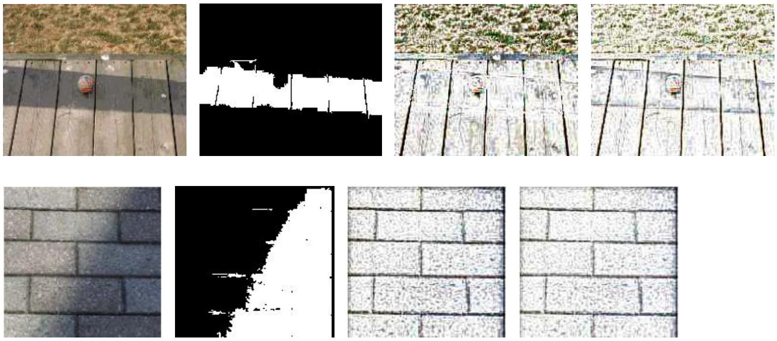


Fig. 5. (*continued*)

In Fig 5, the first column is the original image, the second one is the extracted shadow, the third one is the image in which the shadows are removed by our approach, and the last one is the output image only dealt with Kimmel Retinex algorithm in order to compare with our approach. The comparison of the third column and the last column shows that our approach is feasibility. It can remove both umbra and penumbra regions in the images.

6 Conclusion

The problem of extracting and removing shadows from solo image is an ill-posed problem. But the properties of illumination provide us a cue to solve the problem. In the paper, we describe the methods of shadow detection and removal from solo natural image based on Retinex theory. Unlike the previous methods, we do not make much assumption on shadows' properties; instead we testify the feasibility and validity of our method of detecting and removing both penumbrae and umbrae in the images. In future, how to extract and remove shadows more efficiently and more reliable is our investigation goal.

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