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2 authors:

Saritha Murali
National Institute of Technology Calicut

Govindan V K

BULGARIAN ACADEMY OF SCIENCES

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Shadow Detection and Removal from a Single Image Using LAB Color Space

Saritha Murali, V. K. Govindan***

** M. Tech., Computer Science and Engineering, NITC, Calicut, India*
***Professor, Computer Science and Engineering, NITC, Calicut, India*
Emails: saritha.mkv@gmail.com vkg@nitc.ac.in

Abstract: *A shadow appears on an area when the light from a source cannot reach the area due to obstruction by an object. The shadows are sometimes helpful for providing useful information about objects. However, they cause problems in computer vision applications, such as segmentation, object detection and object counting. Thus shadow detection and removal is a pre-processing task in many computer vision applications. This paper proposes a simple method to detect and remove shadows from a single RGB image. A shadow detection method is selected on the basis of the mean value of RGB image in A and B planes of LAB equivalent of the image. The shadow removal is done by multiplying the shadow region by a constant. Shadow edge correction is done to reduce the errors due to diffusion in the shadow boundary.*

Keywords: *Shadow detection, shadow removal, LAB colour space, illumination, reintegration.*

1. Introduction

The obstruction of light by objects creates shadows in a scene. An object may cast a shadow on itself, called self-shadow. The shadow areas are less illuminated than the surrounding areas. In some cases the shadows provide useful information, such as the relative position of an object from the source. But they cause problems in computer vision applications like segmentation, object detection and object counting. Thus shadow detection and removal is a pre-processing task in many computer vision applications. Based on the intensity, the shadows are of two types

– hard and soft shadows. The soft shadows retain the texture of the background surface, whereas the hard shadows are too dark and have little texture. Thus the detection of hard shadows is complicated as they may be mistaken as dark objects rather than shadows.

Most of the shadow detection methods need multiple images for camera calibration. But the best technique must be able to extract shadows from a single image. Also it is difficult to distinguish dark objects and shadows from a single image. This paper gives a simple method to detect and remove shadows from a single RGB image. A shadow detection method is selected based on the mean value of the RGB image in A and B planes of LAB equivalent of the image. The shadow removal is done by multiplying the shadow region with a constant. The illumination is not uniform in a shadow region. Towards the shadow boundary, diffusion takes place. Thus filtering is done to reduce the errors in the shadow boundary.

2. Previous works

Shadow detection and removal is an important pre-processing task in many of the computer vision applications. The shadows may give rise to false segments in the image segmentation process. Also, shadows may be wrongly detected as objects in object detection algorithms. Various pixel-based and region-based methods were proposed to detect the shadows in an image. This section briefly reviews some of the important research works in shadow detection and removal.

Shadow areas are lesser illuminated than the surroundings. F i n l a y s o n, H o r d l e y and D r e w [1] proposed a method to locate the shadows by generating an illumination-invariant image, in which the shadows do not appear. The illumination-invariant image is used with the original colour image to locate the shadow edges. These edges are set to zero and the edge representation is reintegrated to get the shadow-free image. Removal of shadows using multiple Retinex paths was proposed in [2]. Reintegration by solving Poisson equation and using a large number of random paths in retinex method are both computationally expensive.

A faster method for shadow removal by averaging the results of reintegration along a few numbers of Hamiltonian paths in the image was proposed in [3]. F r e d e m b a c h and F i n l a y s o n [4] proved that the error propagation during reintegration can be reduced by closing the shadow edges before reintegration. Reintegration is done along Hamiltonian paths in the image that enters and leaves the shadow region only once. But reintegration using Poisson equation [1] gives better results.

In [5] the shadow removal is achieved in three stages. A 1D shadow-free illumination invariant image is created. From this, a 2D color representation is derived and then a 3D shadow-free color image is generated. The shadow edges are finally corrected by inpainting. F r e d e m b a c h and F i n l a y s o n [6] suggested that the shadow regions differ from the non-shadow representation by a single constant which can be calculated in a little time. The constant for R, G and B channels are calculated separately. The constant is such that the addition of the shadow region with the constant will reduce the difference between the shadow region and the surroundings.

X u, Q I, and J i a n g [7] proposed a method to detect vague shadows in an image using derivatives of the input image. The hard shadows are detected using colour invariant image. A shadow-free image is reconstructed by reintegration using Poisson equation. A method to remove the shadows from curved areas retaining the background texture is proposed in [8]. The removal of shadows is achieved by calculating different scale factors for shadow regions and penumbra regions to cancel the effect of shadows.

F i n l a y s o n, D r e w, and L u [9] proposed that the shadows can be removed by minimizing entropy. The distribution of pixels with less entropy can be achieved by taking 1D projection in the correct invariant direction. The detection of shadows is more complicated in the case of monochromatic images, than colour images. An approach to extract shadows from an image using the information supplied by the user is proposed in [10]. The image is segmented and the shadow, non-shadow and background regions are interactively specified by the user. The shadow removal is achieved by graph cut algorithm.

Z h u et al. [11] proposed a method to detect the shadows in single monochromatic image using a shadow invariant, shadow variant and near-black features. In [12], trained decision tree classifier is used to detect the shadow edges in outdoor images. The shadow edges are then grouped by a Conditional Random Field (CRF) based optimization. A region-based approach to detect and remove the shadows from an image was proposed by G u o, D a i, and H o i e m [13]. The segmented regions in the image are classified based on relative illumination and using a graph-cut, the labeling of the shadow and non-shadow regions is done. The lighting of shadow-pixels is done to recover a shadow-free image.

A method to detect the shadows in a single image using a Tricolor Attenuation Model (TAM) was proposed in [14]. The shadow identification is done followed by generation of an invariant image on which segmentation is performed. TAM is then used to detect the shadow. But the dark areas are misclassified as shadows. S a l v a d o r, C a v a l l a r o, and E b r a h i m i [15] proposed a method to identify and classify the shadows in colour images. Luminance and colour information are used to detect shadows. This method also classifies the shadows as self or cast shadows. But restrictions are placed on the light source for the method to work efficiently. In [16] the shadow removal is done by illuminating the shadow region till it gets the same illumination as the surroundings. The texture is retained. The shadow removal is done using energy function in [17], assuming that the lighting needed in the shadow region is a constant.

Most of the works on shadow removal need multiple images and calibrated camera. Methods like reintegration using Poisson equation are time intensive. Also, dark objects are often mistaken as shadows. A simple method to detect and remove the shadows from a single RGB image is proposed in this paper. Shadow detection, shadow removal and shadow edge correction are the main stages in this approach. A shadow detection method is selected based on the mean value of RGB image in A and B planes of LAB equivalent of the image. The shadow removal is done by multiplying the shadow region by a constant. The illumination is not uniform in the shadow region. Towards the shadow boundary, diffusion takes place. Thus, shadow edge correction is done to reduce the errors in the shadow boundary.

The paper is organized as follows: Shadow detection method is described in Section 3, and the shadow removal is presented in Section 4. Section 5 deals with the correction of shadow edges. The experimental results are presented in Section 6, and finally the approach is concluded in Section 7.

3. Shadow detection

The shadows appear in areas where the light from a source does not reach directly due to obstruction by some object. An object can also cast a shadow on itself. In this work, shadow detection is done in LAB colour space. Initially the RGB image is converted to its LAB equivalent image. Then, based on the mean value of the image in A and B planes, one of the methods is selected for shadow detection.

3.1. The LAB colour space

The LAB colour space has three channels – L is the Lightness channel, A and B are the two colour channels. The L channel has values ranging from 0 up to 100, which correspond to different shades from black to white. The A channel has values ranging from −128 up to +127 and gives the red to green ratio. The B channel also has values ranging from −128 up to +127 and gives the yellow to blue ratio. Thus, a high value in A or B channel represents a colour having more red or yellow and a low value represents a colour having more green or blue. Fig. 1 gives a pictorial representation of the LAB color space.

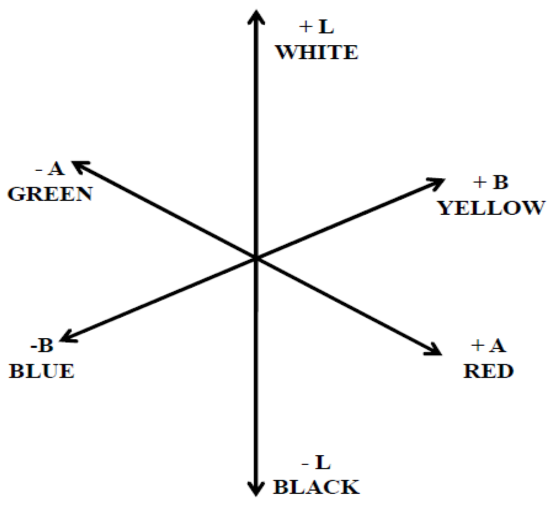


Fig. 1. Illustration of the LAB colour space [18]

3.2. Shadow detection

Shadows appear in areas where the light from a source does not reach directly due to obstruction by some object. An object can also cast a shadow on itself. An approach to detect the shadows areas in a single RGB image was proposed in [19]. The colour image is converted from RGB to LAB colour space. Since the shadow regions are darker and less illuminated than the surroundings, it is easy to locate them in the L channel since the L channel gives lightness information. The B channel values are also lesser in the shadow areas in most of the outdoor images. Thus combining the values from L and B channels, the pixels with values less than a threshold are identified as shadow pixels, and others as non-shadow pixels. The method works well only for images whose yellow to blue ratio is maintained within a range.

In this paper we attempt to overcome the disadvantages in [19]. The shadow detection is done in LAB colour space. The RGB image is initially converted to a LAB image. The mean value of the image in A and B channels are calculated. When the sum of the mean values in A and B channels is less than a threshold (in the experiments, the threshold set is 256), the method proposed in [19] works better. But when the mean value is greater, then a different method is employed. Pixels with a value in L channel less than the difference of the mean value in L channel and one-third of the standard deviation in L channel are classified as shadow pixels. Other pixels are identified as non-shadow pixels.

The major steps involved in the shadow detection phase are:

1. Convert the RGB image to a LAB image.

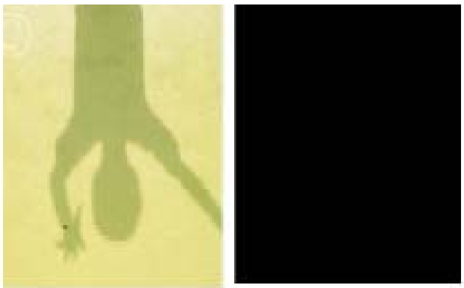
2. Compute the mean values of the pixels in L, A and B planes of the image separately.

3. If mean (A) + mean (B) $\leq$ 256

3.1. Classify the pixels with a value in L $\leq$(mean(L) − standard deviation (L)/3) as shadow pixels and others as non-shadow pixels.

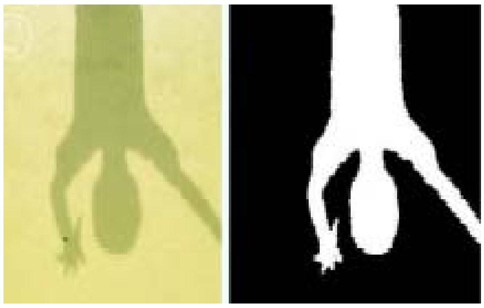
4. Else classify the pixels with lower values in both L and B planes as shadow pixels and others as non-shadow pixels.

The shadow detection using this pixel-based method may classify some non shadow pixels as shadow pixels. Isolated pixels are removed using morphological operation called cleaning. The misclassified pixels are removed using dilation followed by erosion. Also area-based thresholding is done, so that only regions with a number of pixels greater than a threshold can be considered as shadow regions. All these morphological operations thus help to eliminate misclassification of pixels. Fig. 2 gives a failure case of the method proposed in [19] where a shadow region is not detected. Fig. 3 gives the shadow area detected using the proposed method.



(a) (b)

Fig. 2. Failure case of the method proposed in [19]: original image (a); a shadow region is not detected (b)



(a) (b)

Fig. 3. A shadow area detected using the proposed method: original image (a); the detected shadow region shown as white (b)

4. Shadow removal

Shadow removal is done by multiplying R, G and B channels of the shadow pixels using appropriate constants [19]. Each shadow region is considered separately. The ratio of the average of each channel in the near non-shadow region to that in the shadow region is taken as a constant for each channel. The shadow regions achieve almost the same illumination as the non-shadow regions. But over-illumination may occur towards the edges of shadow.

5. Shadow edge correction

Since shadow regions are not uniformly illuminated, the same constant for the entire shadow region will create over-illuminated areas near the shadow edges. This is overcome by applying a median filter on the over-illuminated areas. Thus a shadow-free image without over-illuminated edges is obtained.

6. Experimental results

The shadow detection and removal module was implemented in MATLAB R2010a Version.7.10. The entire process was tested over real images obtained from a data set proposed in [11]. No assumption is made on the lighting conditions. The time for an RGB image of the size of 256×256 is less than 5 s. The shadow region is almost of the same illumination as the non-shadow areas. The results of the comparison of this method with the method proposed in [19] are given in Fig. 4. The values of L, A and B channels are mapped in the range from 0 up to 255 in these experiments.

Table 1 gives details of the images in Fig. 4. For the first two images, the sum of the mean values in A and B planes are greater than the threshold (256). So for these images, the classification based on the pixel value in L channel is done. The classification, based on L and B values does not give any result for these images. For the next two images, the sum of the mean values is lesser than the threshold. Thus the classification based on the pixel values in both L and B planes is used for these images. Classification using the values in L channel alone does not give satisfactory results for these images. Thus, the proposed approach gives good detection results for outdoor images and overcomes the disadvantage of the method proposed in [19]. Some of the shadow removal results are shown in Fig. 5.

(a) (b) (c)

Fig. 4. Shadow detection results: original images (a); classification based on the pixel value in L channel (L less than or equal to ((mean(L)-standard deviation(L)/3) as shadow pixels) (b); classification based on the pixel values in both L and B planes (L, B less than a threshold as shadow pixels) (c)

Table 1. Details of the images in Fig. 4

Image	Mean(A)	Mean(B)	Mean(A) + mean(B)
Image 1	121	166	287
Image 2	122	150	272
Image 3	128	120	248
Image 4	123	127	250

(a) (b) (c)

Fig. 5. Results of the shadow detection and removal algorithm: original images containing a shadow (a); shadows detected shown in white (b); output of the proposed method (c)

7. Conclusion

A method to detect and remove shadows from a single RGB image is proposed. A shadow detection method is selected on the basis of the mean values of A and B channels of the LAB image. The shadow removal is done by multiplying the shadow regions by a constant. Finally the shadow edge is corrected by using filters. The shadow removal technique proposed in this paper gives fast results and does not need multiple images or camera calibration. A problem with this approach is that the dark objects are misclassified as shadow areas. The performance can be improved further by employing region-based techniques as in [11] to recover the shadow region.

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