Shadow Detection and Removal Based on YCbCr Color Space

Article *in* The Smart Computing Review · February 2014

DOI: 10.6029/smartcr.2014.01.003

Deb Kaushik
Chittagong University of Engineering & Technology

Ashraful Huq Suny
Chittagong University of Engineering & Technology

Smart Computing Review

Shadow Detection and Removal Based on YCbCr Color Space

Kaushik Deb and Ashraful Huq Suny

Dept. of CSE, Chittagong University of Engineering & Technology (CUET) / Chittagong-4349, Bangladesh /debkaushik99@cuet.ac.bd, a_suny08@yahoo.com

* Corresponding Author: Kaushik Deb

Received November 16, 2013; Revised January 12, 2014; Accepted January 19, 2014; Published February 28, 2014

Abstract: Shadows in an image can reveal information about the object's shape and orientation, and even about the light source. Thus shadow detection and removal is a very crucial and inevitable task of some computer vision algorithms for applications such as image segmentation and object detection and tracking. This paper proposes a simple framework using the luminance, chroma: blue, chroma: red (YCbCr) color space to detect and remove shadows from images. Initially, an approach based on statistics of intensity in the YCbCr color space is proposed for detecting shadows. After the shadows are identified, a shadow density model is applied. According to the shadow density model, the image is segmented into several regions that have the same density. Finally, the shadows are removed by relighting each pixel in the YCbCr color space and correcting the color of the shadowed regions in the red-green-blue (RGB) color space. The most salient feature of our proposed framework is that after removing shadows, there is no harsh transition between the shadowed parts and non-shadowed parts, and all the details in the shadowed regions remain intact. Various shadow images were used with a variety of conditions (i.e. outdoor and semi-indoor) to test the proposed framework, and results are presented to prove its effectiveness.

Keywords: Shadow detection, Shadow removal, YCbCr color space, Morphological operation, Color histogram, Gaussian smoothing

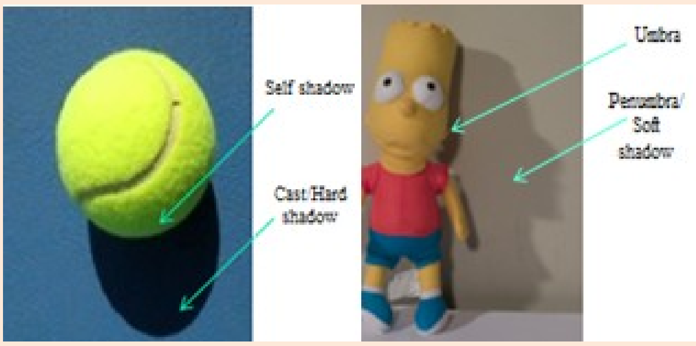
Introduction

Shadows are physical phenomena observed in most natural scenes. Shadows and shadings in images lead to undesirable problems on image analysis. Moreover, shadows imply a geometric relationship between objects, light source, and viewpoint. This means that real images including shadows are used for image synthesis only in a limited situation where the lighting condition is consistent with that of the real image. That is why much attention has been paid to the area of shadow detection and removal over the past decades, covering many specific applications, such as traffic surveillance face recognition and image segmentation.

DOI: 10.6029/smartcr.2014.01.003

Shadows can be defined as the parts of the scene that are not directly illuminated by a light source due to an obstructing object or objects. The shadow regions, however, are illuminated by ambient light. Typically, shadows can be divided into two major classes (self-shadows and cast shadows), as depicted in Figure 1(a). A self-shadow occurs on the portion of an object that is not illuminated by direct light. A cast shadow is the area projected by the object in the direction of direct light. The cast shadow is usually further divided into two parts, umbra and penumbra, as shown in Figure 1(b). The umbra represents the shadow region where the primary light source is completely obscured, whereas the penumbra is the region around the edge of a shadow where the light source is only partially obscured.

Again, based on the intensity, the shadows are of two types (hard and soft shadows), as depicted in Figure 1. 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 because they can be mistaken for dark objects rather than shadows. Though most of the shadow detection methods need multiple images for camera calibration, the best technique must be able to extract shadows from a single image. This paper proposes a simple framework using the luminance, chroma: blue, chroma: red (YCbCr) color space to detect and remove shadows from shadow images.



(a) (b)

Figure 1. Classification of shadows: (a) self and cast shadows, (b) umbra and penumbra

In this framework, a simple method has initially been proposed, which requires intensity information in the YCbCr color space for shadow detection. Then the image is segmented according to shadow density. Finally, the shadows are removed by relighting each pixel in the YCbCr color space. In addition, the colors of the recovered region are corrected in the red-green-blue (RGB) color space.

The rest of the paper is organized as follows. Section II lists and defines related terms. In Section III, related works on shadow detection and removal techniques are reported and briefly described. In Section IV, the proposed shadow detection and removal framework is described. Section V presents the experiment results and compares the proposed framework with two other existing methods, outlining differences and similarities. Finally, Section VI outlines the conclusions and possible future directions from this work.

Related Terms

■ Morphological Operation

Morphological image processing is a collection of operations related to the shape or morphology of features in an image. Morphological operations are applied in order to remove noise and discontinuities from the extracted foreground. Two basic operations are erosion and dilation. A matrix of arbitrary size consisting of only 0's or 1's, called template or structuring elements, is used to perform these operations. Dilation bridges the gap in the image, and erosion removes unwanted details in the image.

■ Gaussian Smoothing

Gaussian smoothing is the result of blurring an image by a Gaussian function. Gaussian smoothing is used as a preprocessing stage in order to enhance image structures at different scales. The Gaussian smoothing operator is a two-dimensional (2D) convolution operator that is used to `blur' images and remove detail and noise. In this sense it is similar to the mean filter, but it uses a different kernel that represents the shape of a Gaussian (`bell-shaped') hump. Gaussian filtering is done by convolving each point in the input array with a Gaussian kernel and then summing them all to produce the output array.

■ Color Histogram

A color histogram represents the number of pixels that have colors in each of a fixed list of color ranges that span the image's color space (the set of all possible colors). Like other kinds of histograms, the color histogram is a statistic that can be viewed as an approximation of an underlying continuous distribution of color values.

Related Works

It is easier for the human eye to distinguish shadows from objects. However, identifying shadows by computer is a challenging research problem. It is therefore of great importance to discover ways of properly detecting shadows and removing them while keeping other details of the original image intact. A significant amount of research has been performed on detecting and removing shadows over the past few years.

The tricolor attenuation model (TAM) was proposed [1] to detect shadows in a single image. Shadow identification was done, followed by generation of an invariant image, on which segmentation was performed. TAM was then used to detect the shadows, but dark areas were misclassified as shadows. Shadow detection was done using a hypothesis test, and shadow removal was done using an energy function [2], assuming that the lighting needed in the shadow region is a constant. But there were harsh transitions between shadow and non-shadow regions in the shadow-free image. An entropy minimization technique was introduced [3] for removing shadow. However, the shadow-removal results were not satisfactory. In other research, shadow removal was achieved in three stages [4]. First, a 1D shadow-free illumination invariant image was created, from which a 2D color representation was derived, and then, a 3D shadow-free color image was generated. Then, the shadow edges were corrected. A region-based approach to detect and remove the shadows from an image was proposed [5]. The segmented regions in the image were classified based on relative illumination and using a graph cut. Then the labeling of the shadow and non-shadow regions was done, and the lighting of shadow pixels was done to recover a shadow-free image. Here, initial segmentation was mandatory for the shadow detection method. Shadow removal has been done by illuminating the shadow region until it has the same illumination as the surroundings [6]. Then the texture was reinstated. They used color and near infrared images for shadow detection and removal. Another method to detect the shadows in a single monochromatic image using shadow invariant, shadow variant, and near-black features was proposed [7], but this method could not remove the shadows. A hierarchical graph cut was introduced for removing shadows [8]. Another method to remove shadows from curved areas, but that retained the background texture, was proposed [9]. The removal of shadows was achieved by calculating different scale factors for shadow regions and penumbra regions to cancel the effects of shadows. A faster method for shadow removal by averaging the results of reintegration along a few numbers of Hamiltonian paths in the image was proposed [10]. A method to detect vague shadows in an image using derivatives of the input image was described [11]. The hard shadows were detected using a color invariant image. However, the method could not identify soft shadows properly. In this method, a shadow-free image was reconstructed by reintegration using a Poisson equation. Fredembach and Finlayson [12] suggested that shadow regions differ from the non-shadow representation by a single constant, which could be calculated. The constant for R, G, and B channels were calculated separately. The constant was such that the addition of the shadow region with the constant would reduce the difference between the shadow region and the surroundings. Here, inverse Fourier transforms that were four times the size of the image, were required for 2D reintegration, and several different Hamiltonian paths were required for 1D reintegration. However, error propagation during reintegration can be reduced by closing the shadow edges before reintegration [13]. A shadow density model was introduced by Baba and Asada [14]. This model could not, however, remove shadows from non-homogeneous images. Another method, which used an illumination-invariant image with the original color image to locate the shadow edges, was proposed [15]. Those edges were set to zero, and the edge representation was reintegrated to get a shadow-free image. This method could work quite well with high-quality images and calibrated sensors, but often performed poorly for typical web-quality consumer photographs.

Most of the works on shadow removal need multiple images and a calibrated camera. Methods like reintegration using a Poisson equation are time consuming. Also, dark objects are often mistaken as shadows. So, this paper proposes a simple method based on the YCbCr color space to detect and remove shadows. Initially, shadow detection is achieved by focusing on the Y channel and calculating its intensity. Then, shadow removal is achieved by pixel relighting and color correction.

Proposed Framework

■ Shadow Detection

The shadow detection process can be a primary step for compensation of the shadows, followed by an eventual step of image analysis tasks (such as object recognition), or it can be a fundamental step where the detection results are directly used in 3D shape estimation or similar tasks. In any case, shadow detection is an initial process for a final image analysis task. Hence, the performance of the final task is highly dependent on shadow detection performance. The proposed framework for shadow detection is depicted in Figure 2.

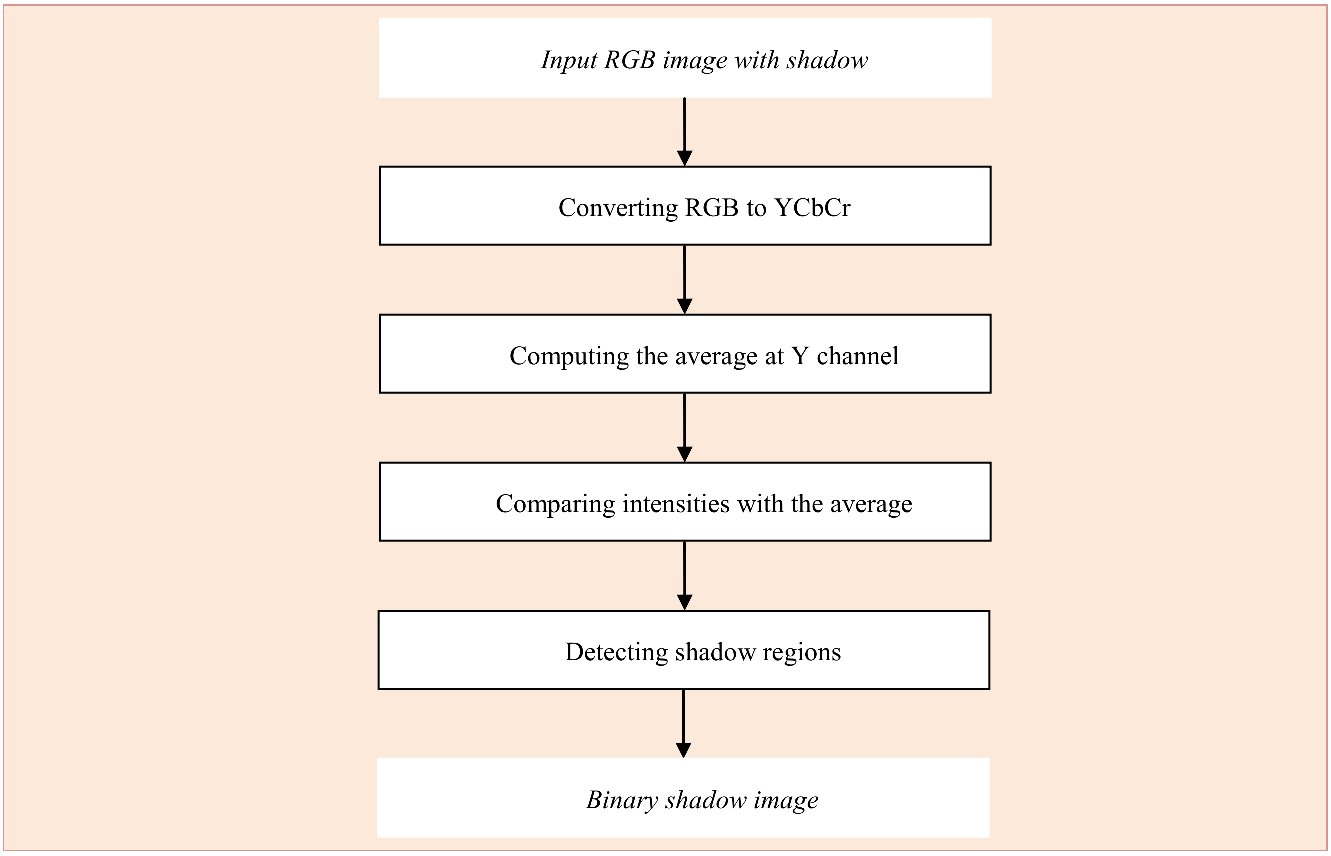


Figure 2. The proposed framework for shadow detection

An approach based on statistics of intensity is presented for shadow detection. Initially the RGB image is converted to an equivalent YCbCr image. In the YCbCr color space, the Y represents luminance information while Cb and Cr represent the color information. Next, focusing on the Y channel, its histogram is computed. Histogram dissension gives us a higher contrast image in the Y channel. After that, the mean of the image in the Y channel is computed. Then sliding-window iteration through the image is performed. The sliding window size is 3×3 matrices. In order to decide which pixels belong to the shadow, two approaches are followed. First, shadow pixels that have intensity less than one standard deviation of the whole image are classified. This step cannot identify the shadow regions properly, as shown in Figure 3(c); some shadow pixels are identified as non-shadow pixels. So next, the non-shadow point's mean and standard deviations for the sliding window are computed. Now, the pixels that have intensity less than the one standard deviation of the windows are considered shadow pixels. Figure 3 portrays a successful shadow detection process via the proposed framework.

In addition, isolated pixels are removed using a morphological operation. The misclassified pixels are removed using dilation followed by erosion. The result of shadow detection gives us a binary shadow mask, which will be used as input for the shadow removal process.

■ Shadow Removal

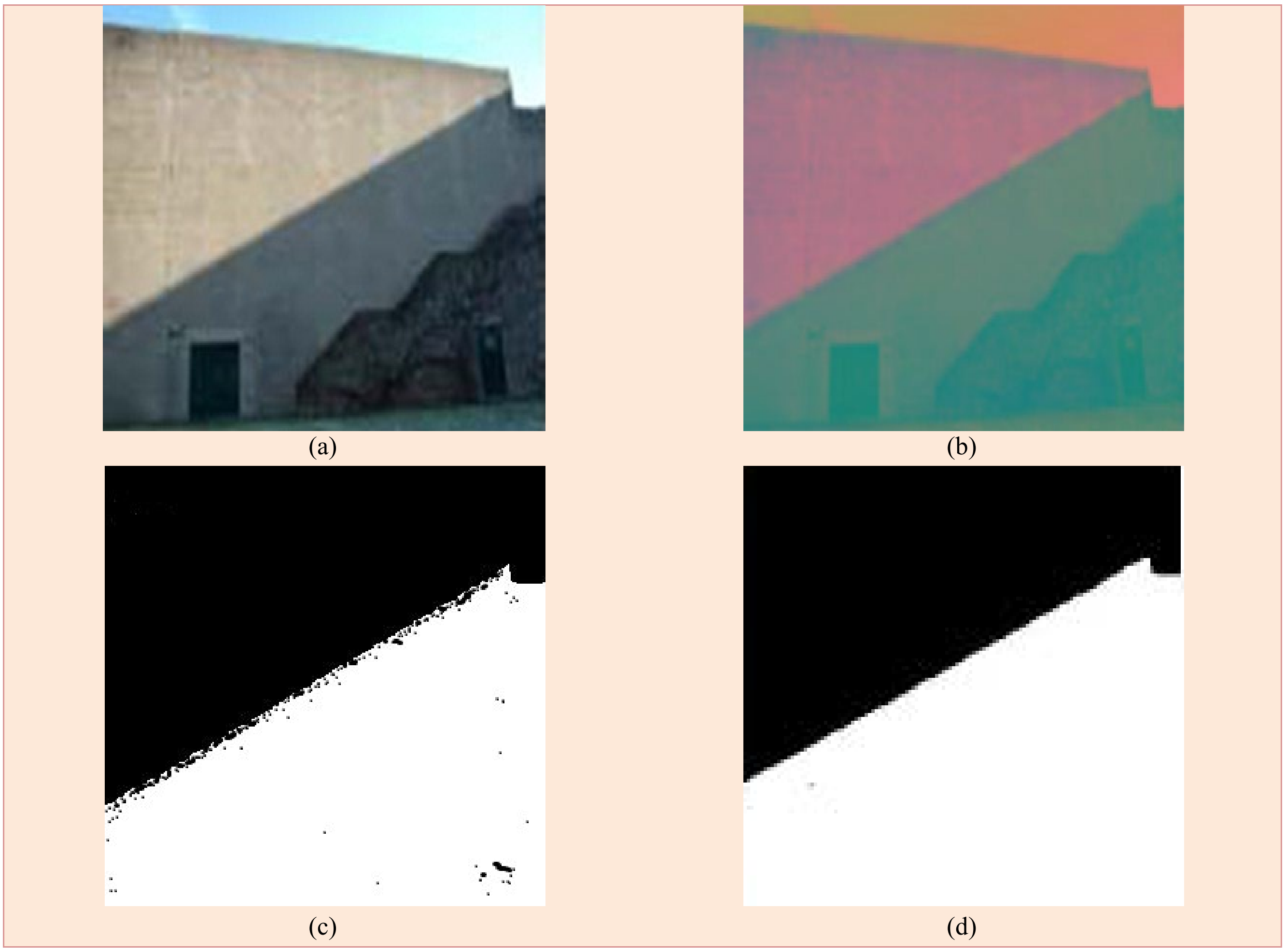
The proposed framework for shadow removal is shown in Figure 4. For shadow removal, a simple shadow model is used, where there are two types of light source: direct and ambient light. Direct light comes directly from the source, while environment light is from reflections off surrounding surfaces. The shadow model can be represented by the following formula:

$$I_\iota = (t_i \cos \theta_\iota L_d + L_e) R_i \tag{1}$$

where I_i represents the value for the i-th pixel, L_d and L_e represent the intensity of the non-shadow pixels and shadow pixels, R_i is the surface reflectance of that pixel, and θ_i is the angle between the direct lighting direction and the surface normal. t_i is the attenuation factor of the direct light; if $t_i = 1$, the object point is in a sunshine region, and if $t_i = 0$, then the object point is in a shadow region. Here, a shadow coefficient for the i-th pixel is denoted by $k_i = t_i \cos\theta_i$, and the ratio between non-shadow pixels and shadow pixels can be calculated as $r = L_d / L_e$.

The shadow detection procedure provides us with a binary shadow mask where each pixel i is assigned a k_i value of either 1 or 0. Based on this model, the goal is to relight each pixel using this coefficient in order to obtain a shadow-free image. The new pixel value is computed based on the following formula:

$$I_i^{shadow\_free} = ((r + 1) / (k_i r + 1)) I_i \qquad (2)$$



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

Figure 3. Illustration of the shadow detection process: (a) input shadow image, (b) converting to a YCbCr image, (c) extracted shadow regions after applying the first approach, and (d) extracted shadow regions after considering non-shadow pixels

Initially, the average pixel intensities in the shadow and non-shadow areas of the image are computed, and this difference is added with the pixels of the Y channel. Then, the ratio between average shadow pixels and average non-shadow pixels is computed. Next, Cb and Cr values are computed. After that the image is converted to an RGB image, as shown in Figure 5(c). Because of the ambient light, the ratios of the two pixels are not same in all three color channels. These two pixels will be different not only in intensity, but also in hue and saturation. Thus, correcting just the intensity of the shadowed pixels does not remove the shadow, and we need to correct the chromaticity values as well.

Applying global brightness, the shadow density is calculated, which shows the degree of the light's effect. It becomes 0 in a sunshine region, and becomes 1 in an umbra region. Using the shadow density, the shadow area is segmented into sunshine, penumbra and umbra regions. Since the lighting color of the umbra region is not always the same as that of the sunshine region, the color adjustment is performed between them. Then, the color average and variance of the umbra region are adjusted to be the same as those of the sunshine region. In the penumbra, color and brightness adjustments for small regions are performed the same as they are for the umbra region. Finally, all boundaries between shadowed regions and neighboring lit regions are smoothed by convolving them with a Gaussian mask, as depicted in Figure 5(d). Figure 5 portrays a successful shadow removal process via the proposed framework.

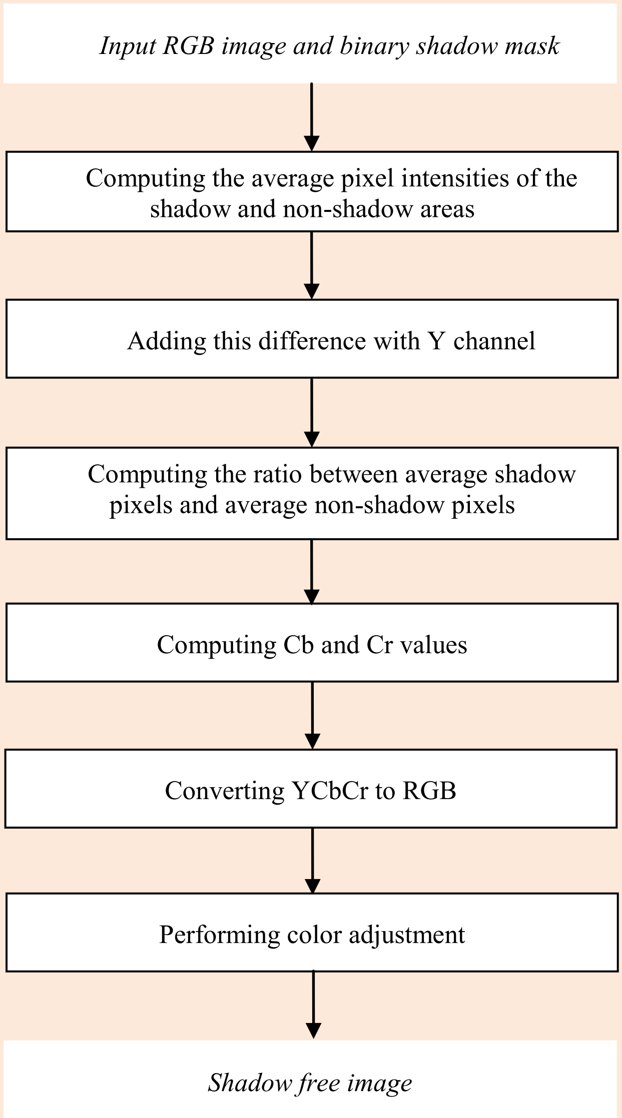


Figure 4. The proposed framework for shadow removal

(a) (b)

(c) (d)

Figure 5. Illustration of shadow removal process: (a) original image, (b) after pixel relighting in YCbCr, (c) after converting to RGB, and (d) after color correction and smoothing

(a) (b)

Figure 6. Examples of shadow detection using the proposed framework: column (a) depicts the original image, and column (b) depicts the detected shadow regions

Experiment Results and Analysis

The shadow detection and removal module is implemented in the MATLAB environment. An Intel Pentium Dual Core 2.20 GHz machine with a 32-bit operating system and 1 GB RAM was used for testing. In the experiments, images sized 256×256 were used. The training set consisted of 40 outdoor images and 20 indoor images. Some examples of shadow detection and shadow removal under the proposed framework are shown in Figure 6 and Figure 7.

The first two rows of Figure 6 show shadow detection results from outdoor images, and the last row of Figure 6 shows the shadow detection result from an indoor image after applying the proposed shadow detection framework. Hence, the proposed framework is capable of detecting shadows in both cases.

Figure 7(b) shows a shadow-free image from the proposed shadow removal framework. We see that the proposed framework can successfully remove the shadow regions.

(a) (b)

Figure 7. Examples of shadow removal by using the proposed framework: column (a) depicts the original image, and column (b) depicts the shadow-free image

Column (a) of Figure 8 shows the input images with shadow, and column (b) shows the output shadow-free images [2, 14], where some shadowed surfaces in the images still do not look similar to the lit areas. Finally, column (c) of Figure 8 shows the removed shadow regions using proposed framework. It is clearly seen from column (c) of Figure 8 that the texture of the surface that was under the shadow is preserved, and there is no harsh transition between the shadowed and non-shadowed parts.

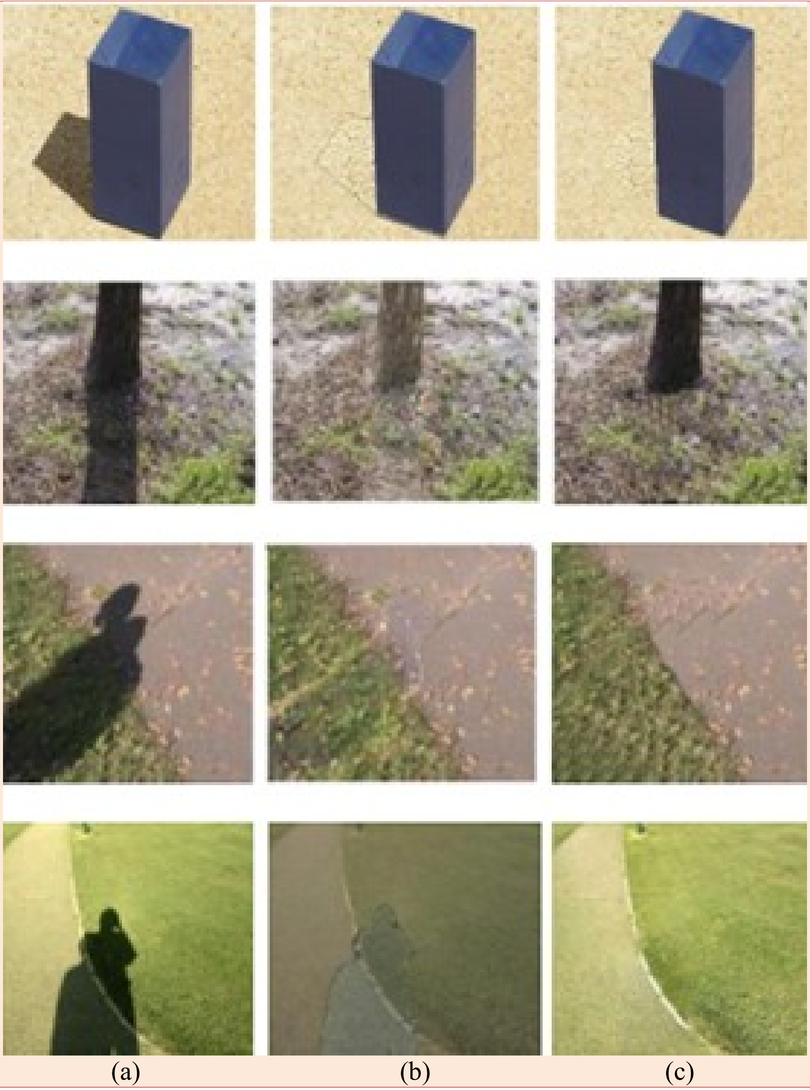


Figure 8. Comparison of proposed framework with methods by Kumar and Kumar and Baba and Asada [2, 14]: (a) original images, (b) recovered shadow-free images [2, 14], and (c) recovered shadow-free images using the proposed framework

A comparison between the proposed framework and some well-reported methods in the literature is given in Table 1. From Table 1, we see that the proposed framework outperforms the methods of Kumar and Kumar [2] and Baba and Asada [14] in both detection and removal rates. The average computation time for shadow detection and shadow removal under the proposed framework are 0.0446 s and 0.6207 s, respectively, as shown in Table 2.

Table 1. Comparison of detection and removal rates

Framework	***Shadow detection rate***	***Shadow removal rate***
Kumar and Kumar [2]	86.2%	82.4%
Baba and Asada [14]	82.5%	81.2%
The proposed method	91.66%	89.5%

Table 2. Comparison of average computation time

Framework	***Average computation time for shadow detection (seconds)***	***Average computation time for shadow removal (seconds)***
Kumar and Kumar [2]	0.0880	0.9236
Baba and Asada [14]	0.0674	0.8209
The proposed method	0.0446	0.6207

Conclusion

This paper delineates a shadow detection and removal method based on the YCbCr color space. Most of the earlier works involved multiple images, along with a calibrated camera, whereas the proposed method is a simple and efficient way to remove shadows from single images. Analysis and experiment results suggest that the proposed shadow detection and removal framework is more precise than methods by Kumar and Kumar [2] and Baba and Asada [14]. Moreover, the proposed framework outperforms Kumar and Kumar [2] and Baba and Asada [14] because of faster computation time, and is more precise and easily implemented. In addition, the emphasis of this paper is on the implementation of a new method to detect and remove shadows using the YCbCr color space. And emphasis is also given to improving the recovered shadow-free image by correcting color. The main achievement of the proposed framework lies in the absence of harsh transitions between shadowed and non-shadowed parts, while keeping all other details intact. It is evident that the proposed framework effectively succeeded in removing shadows from multiple textured images. While conducting the experiments, different viewpoints, illumination conditions and varied distances between object and camera often occurred. We leave these issues for further studies.

References

[1] K. E. E. Rani, G. Jemilda, "Shadow detection in single still images using TAM based multi-step algorithm," *International Journal of Computer Science and Technology,* vol. 2, no. 4, 2011.
[2] S. Kumar, A. Kumar, "Shadow detection and removal in color images using Matlab," *International Journal of Engineering Science and Technology*, vol. 2, no. 9, pp. 4482-4486, 2010.
[3] G. D. Finlayson, M. S. Drew, L. Cheng, "Entropy minimization for shadow removal," *International Journal of Computer Vision*, vol. 85, no. 1, pp. 35-57, 2009. Article (CrossRef Link)
[4] G. D. Finlayson, S. D. Hordley, L. Cheng, M. S. Drew, "On the removal of shadows from images," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, pp. 59-68, 2006. Article (CrossRef Link)
[5] R. Guo, Q. Dai, D. Hoiem, "Single image shadow detection and removal using paired regions," in *Proc. of the 18th IEEE CVPR*, pp. 2033-2040, 2011.
[6] A. Germain, N. Salamati, S. Susstrunk, "Removing shadows from images using color and near-infrared," in *Proc. of the IEEE ICIP*, pp. 1713-1716, 2011. Article (CrossRef Link)
[7] J. Zhu, K. G. G. Samuel, S. Z. Masood, M. F. Tappen, "Learning to recognize shadows in monochromatic natural images," in *Proc. of the IEEE CVPR,* pp. 223-230, 2010. Article (CrossRef Link)
[8] D. Miyazaki, Y. Matsushita, K. Ikeuchi, "Interactive shadow semoval from a single image using hierarchical graph cut," in *Proc. of 9th ACCV*, 2010. Article (CrossRef Link)
[9] E. Arbel, H. Hel-Or, "Texture-preserving shadow removal in color images containing curved surfaces," in *Proc. of the IEEE CVPR*, 2007. Article (CrossRef Link)
[10] C. Fredembach, G. D. Finlayson, "Simple shadow removal," in *Proc. of the 18th ICPR*, vol. 1, pp. 832-835, 2006.
[11] L. Xu, F. Qi, R. Jiang, "Shadow removal from a single image," in *Proc. of the 6th International Conference on Intelligent Systems Design and Applications*, vol. 2, pp. 1049-1054, 2006. Article (CrossRef Link)
[12] C. Fredembach, G. D. Finlayson, "Hamiltonian path-based shadow removal," in *Proc. of the 16th British Machine Vision Conference,* vol. 2, pp. 502-511, 2005.
[13] C. Fredembach, G. D. Finlayson, "Fast re-integration of shadow free images," in *Proc. of the IS&T/SID 12th Color Imaging Conference*, pp. 117-122, 2004.
[14] M. Baba and N. Asada, "Shadow removal from a real picture," in *Proc. of the SIGGRAPH*, 2003.
[15] G. D. Finlayson, S. D. Hordley, M. S. Drew, "Removing shadows from images," in *Proc. of the 7th ECCV*, pp. 823-836, 2002.

Kaushik Deb received the B. Tech., and M. Tech. degrees from Department of Computer Science and Engineering of Tula State University, Tula, Russia, in 1999 and 2000, respectively. He received his Ph.D. degree in Electrical Engineering and Information System from University of Ulsan, Ulsan, South Korea, in 2011. Since 2001, he has been serving as a faculty member in Department of Computer Science and Engineering, Chittagong University of Engineering and Technology (CUET), Chittagong, Bangladesh. He is currently an Associate Professor and Head of the Department of Computer Science and Engineering, Chittagong University of Engineering & Technology(CUET), Bangladesh. His research interest includes computer vision, pattern recognition, intelligent transportation systems (ITSs) and human - computer interaction.

Ashraful Huq Suny is employed as a Lecturer in the Department of Computer Science & Engineering of Chittagong University of Engineering & Technology (CUET). He received B.Sc. degree in Computer Science & Engineering from Chittagong University of Engineering & Technology (CUET), Bangladesh in 2013. His research interest includes computer vision and pattern recognition.