SHADOW DETECTION USING TRICOLOR ATTENUATION MODEL ENHANCED WITH ADAPTIVE HISTOGRAM EQUALIZATION

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ABSTRACT

Shadows create significant problems in many computer vision and image analysis tasks such as object recognition, object tracking, and image segmentation. For a machine, it is very difficult to distinguish between a shadow and a real object. As a result, an object recognition system may incorrectly recognize a shadow region as an object. So the detection of shadows in images will enhance the performance of many machine vision tasks. This paper implements a shadow detection method, which is based on Tricolor Attenuation Model (TAM) enhanced with adaptive histogram equalization (AHE). TAM uses the concept of intensity attenuation of pixels in the shadow region which is different for the three color channels. It originates from the idea that if the minimum attenuated color channel is subtracted from the maximum attenuated one, the shadow areas become darker in the resulting TAM image. But this resulting image will be of low contrast due to the high correlation among R, G and B color channels. In order to enhance the contrast, adaptive histogram equalization is used. The incorporation of AHE significantly improved the quality of the detected shadow region.

KEYWORDS

Shadow Detection, Tricolor Attenuation Model, Adaptive Histogram Equalization, Intensity Image

1. INTRODUCTION

Shadows in images have long been disruptive to certain computer vision applications such as edge detection, image segmentation, object recognition, video surveillance, and stereo registration. Shadows occur when direct light from a light source is partially or totally occluded by an object. In outdoor scenes, there are mainly two light sources: direct sunlight (regarded as a point light source) and diffuse skylight (regarded as an area light source).

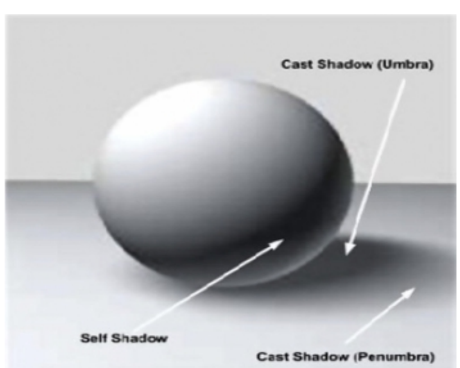


Fig. 1. Types of Shadows

Shadows can be divided into two types: self shadow and cast shadow (shown in fig. 1). The self shadow (also called attached shadow) is the part of an object that is not illuminated by direct light. Cast shadow of an object can be defined as the dark area projected by the object on a surface. Cast shadow can be further divided into umbra and penumbra region. Umbra region is the part of cast shadow where direct light is completely blocked; the penumbra region is the part of a cast shadow where direct light is partially blocked.

Shadows can either aid or challenge the scene interpretation tasks. They are useful in certain kinds of applications such as making flat objects to appear three dimensional, making judgments about local shape and global scene properties, generating constraints on the orientations of surfaces in line-drawings of scenes etc. On the other hand, shadows cause problems in applications where automatic object identification is used such as machine vision. Shadows modify the perceived shape and color of objects or maybe mistakenly recognized as separate objects, because of their well-defined shape and depth. So the removal of shadows from images can significantly improve and facilitate the performance of such applications. In either case, efficient shadow detection is necessary. In this paper we propose a method for detecting cast shadows in outdoor still images.

2. RELATED WORK

The area of shadow detection has made great progress in recent years. Shadow detection methods can be generally classified into property based and physics based techniques. For physics-based techniques, some prior knowledge is needed like geometry and light [1], calibration of the camera [2], or indoor scenes [3]. So the physics-based techniques are usually designed for specific applications, such as moving cast shadow detection [4] and shadow detection in aerial images [5]. Property-based techniques identify shadows through shadow features. Sometimes, only one feature is not enough. For example, shadows usually have lower pixel values, but pixels that have lower values may not be shadows. The useful features for shadow detection are intensity, chromaticity [6, 7], geometry and texture. One of the simple assumptions that can be used for detecting cast shadows is that pixel intensity is very less in the shadow regions since they are blocked directly from the illumination source. But using only this feature is not a reliable method for shadow detection. However it can be used as a first stage to reject non-shadow regions.

According to the input data, shadow detection methods can be classified into moving shadow detection and static image shadow detection. In video sequences, moving shadow detection methods can employ the frame difference technique to locate moving objects and their moving shadows. Prati et al. [8] provided a comparative evaluation of shadow detection methods in video streams. Hsieh et al. [9] provided a novel method to eliminate unwanted pedestrian-like shadows from a static background through Gaussian shadow modeling.

Multiple images can provide more information than single image for shadow detection. So the detection in still images remains a difficult problem. Wu and Tang [10] used the Bayesian approach to extract shadows from a single image, but it needs user intervention. For modeling shadows, Panagopoulos et al. [11] used the Fisher distribution, But it needs 3D geometry information. For detecting ground shadows, Lalonde et al. [12] proposed a learning approach for training decision tree classifier on a set of shadow sensitive features. Another learning-based approach was proposed by Guo et al. [13] for the detection of shadows using paired regions, for a single image. If the parameters are trained well, these learning methods can achieve good performance. However, they will fail when the test image is significantly different from the images in the training set. Another approach based on Tricolor Attenuation model for detecting shadows in single images was proposed in [14]. The algorithm is automatic and simple but it depends upon priori segmentation and the four thresholds which are simply chosen. An improved algorithm which addresses these two problems is proposed in [15].

3. TRICOLOR ATTENUATION MODEL

Fig. 2 shows the formation of a shadow in outdoor scenes [14]. The illumination on non-shadow region is daylight which is a combination of direct sunlight and diffused skylight; that on penumbra is skylight and part of sunlight; and that on umbra is only skylight. Since skylight is a component of daylight, pixel intensity in shadow is lower than that in non-shadow background. i.e., there exists intensity attenuation.

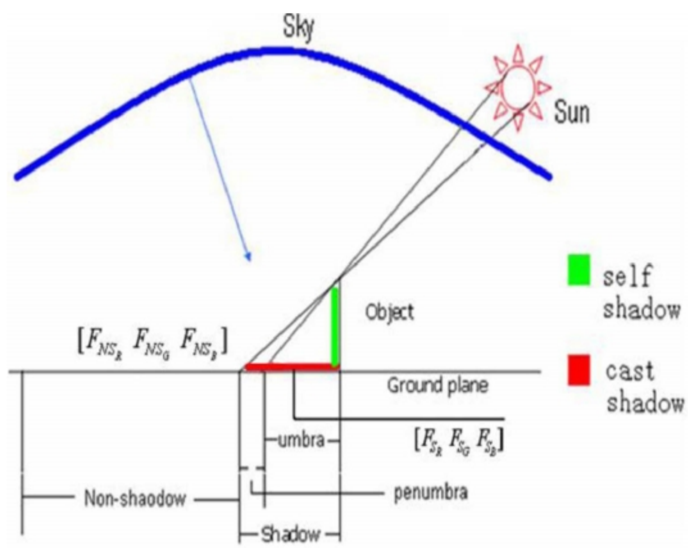


Fig. 2. Shadow occurs when direct light is occluded

Let $[F_{SR}\, F_{SG}\, F_{SB}]$ denotes the pixel value vector of shadow region and $[F_{NSR}\, F_{NSG}\, F_{NSB}]$ as the pixel value vector of the corresponding non-shadow background, the relationship between $[F_{NSR}\, F_{NSG}\, F_{NSB}]$ and $[F_{SR}\, F_{SG}\, F_{SB}]$ is

$$[F_{SR}\, F_{SG}\, F_{SB}] = [F_{NSR}\, F_{NSG}\, F_{NSB}] - [\Delta R\, \Delta G\, \Delta B]$$

Where $[\Delta R\, \Delta G\, \Delta B]$ denotes the tricolor attenuation vector. The relationship among $\Delta R\, \Delta G\ and\ \Delta B$ is called Tricolor Attenuation Model (TAM) [14] which can be used for shadow detection. If $\Delta R\, \Delta G, \Delta B$ are different, the disparities of R, G, B channels of shadow region are different from those of non-shadow region. Let $\Delta R > \Delta G > \Delta B$, if we subtract B channel from R channel:

$$\begin{aligned} F_{SR} - F_{SB} &= F_{NSR} - \Delta R - (F_{NSB} - \Delta B) \\ &= F_{NSR} - F_{NSB} + (\Delta B - \Delta R) \\ &< F_{NSR} - F_{NSB} \end{aligned}$$

Here the disparity between R and B channels of shadow is lower than that of the corresponding nonshadow background. This model originates from the key idea that if we subtract the minimum attenuated channel from the maximum attenuated channel, the results in shadow regions will be lower than the results in nonshadow regions. TAM-based subtraction image (TAM image) is the result of this subtraction. So the shadows will become darker in the resulting TAM image. This is very useful for shadow identification. The relationship among $\Delta R\ \Delta G, \Delta B$ can be represented by:

$$\begin{bmatrix} \Delta R \\ \Delta G \\ \Delta B \end{bmatrix} = \begin{bmatrix} \frac{\Delta R}{\Delta B} . \Delta B \\ \frac{\Delta G}{\Delta B} . \Delta B \\ 1. \Delta B \end{bmatrix} = \begin{bmatrix} m. \frac{F_{NSR}}{F_{NSB}} \\ n. \frac{F_{NSG}}{F_{NSB}} \\ 1 \end{bmatrix} . \Delta B$$

The multistep shadow detection algorithm based on the Tricolor Attenuation Model [14] consists of the following steps:

1. Segment the input image and calculate TAM in each segmented sub-region.
2. Binarizate the TAM images using a threshold, which is the mean value over each sub region. Thus obtain the initial shadows.
3. Verify these shadow regions using the mean values in R, G and B color channels, in each sub-region, as the thresholds.

This shadow detection method works on single still images, even with complex scenes. But still there exists some problems by using this method.

1. It needs segmentation as the pre-processing step.
2. It uses four simply calculated mean values as thresholds.

To overcome these shortcomings another method is proposed [15], in which TAM image and intensity image are combined. This avoids the segmentation step and it is needed to derive only one threshold instead of four simple ones. In this paper we use adaptive histogram equalization to enhance the TAM image and thereby improving the detection results.

4. PROPOSED METHOD

The design of the proposed method is shown in fig.3.

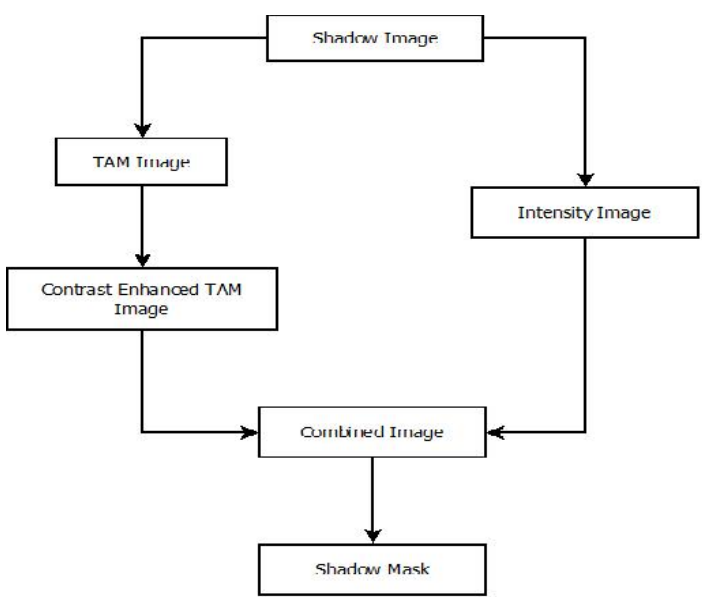


Fig. 3. Block Diagram of the Proposed Method

The method proposed here for shadow detection is based on Tricolor Attenuation Model. It includes three main steps:

1. Obtaining TAM image
2. Enhancing the contrast of the TAM image
3. Combining enhanced TAM image with intensity image

4.1. TAM Image

To obtain TAM image, first the mean values in three color channels of the original image F are calculated

$$[\overline{F_R}\ \overline{F_G}\ \overline{F_B}] = \frac{1}{M}\left(\sum_{k=1}^{M}[F_R^k\ F_G^k\ F_B^k]\right)$$

Where F_R^k denotes the kth pixel of image F in R channel. M is the number of pixels.

(a) (b)

Fig. 4. (a) Input image (b) TAM image

Compare $m.\frac{\overline{F_R}}{\overline{F_B}}$, $n.\frac{\overline{F_G}}{\overline{F_B}}$ and 1 to find the maximum and minimum attenuated color channels. TAM image is formed by subtracting the minimum attenuation channel from the maximum attenuation one.

For example in Fig. 4(a), the tricolor attenuation order for the image is $m.\frac{\overline{F_R}}{\overline{F_B}} > n.\frac{\overline{F_G}}{\overline{F_B}} > 1$. Therefore the corresponding TAM image is formed by subtracting blue channel from the red. ie.R-B.

4.2. Contrast Enhancement

The red, green and blue color channels are highly correlated. So the subtraction of color channels will smooth the pixel values. This smoothing may cause details missing in detection results. Enhancing contrast of the TAM image improves the quality of the detection result. In this paper adaptive histogram equalization is used for contrast enhancement. Fig.5 demonstrates the difference between TAM image and contrast enhanced TAM image.

The difference between AHE and ordinary histogram equalization is that the AHE computes several histograms corresponding to different sections of the image, and uses this information to redistribute the lightness values of the image. Therefore it is suitable for improving the local contrast and bringing out more detail in an image.

Ordinary histogram equalization is more suitable for images where the distribution of pixel values is similar throughout the image. However, when the image contains comparatively lighter or darker regions, the contrast in those regions will not be sufficiently enhanced. AHE transforms each pixel with a transformation function derived from its neighbourhood. Each pixel is transformed according to the histogram of a square surrounding the pixel. The transformation function is proportional to the cumulative distribution function (CDF) of pixel values in the neighbourhood. Fig.5 shows a comparison of TAM images obtained without contrast enhancement (Fig.5-b) and after contrast enhancement using AHE .

(a) (b) (c)

Fig. 5. (a) Input image (b) TAM image (c) Contrast enhanced TAM image

Since we are dealing with the shadow images, the distribution of pixel values will not be similar throughout the image. Therefore AHE is more suitable for contrast enhancement in this application.

4.3. Combining TAM and Intensity Images

Even though TAM provides sufficient information for shadow detection, sometimes it suffers from false detection and details missing problems. TAM based channel subtraction procedure may make not only shadows, but also some other objects darker. For example in Figure 4, the TAM image is formed by subtracting the blue channel from the red channel. Here not only the shadows but also some blue objects (e.g., the flowerpot) become dark. The flowerpot may be falsely classified as a shadow after binarization. Fig. 6 demonstrates this problem if we only employ TAM (without segmentation) to detect shadows [15]. These problems caused by luminance information are lost during the channel-subtraction procedure. But the lost information in the TAM image can be compensated by intensity (grayscale) image. So the TAM image must be combined with intensity image.

(a) (b) (c)

Fig. 6. (a) Input image; (b) Only using TAM; (c) combined TAM and Intensity

Combined image Z is obtained by combing TAM image X with intensity image Y as follows:

$$Z=\alpha X + Y$$

where α is the weight coefficient. We define the objective function as:

$$\zeta(T) = G(T).\left(\overline{Z \cap S^C(T)} - \overline{Z \cap S(T)}\right)$$

where S(T) denotes the shadow determined by a threshold T. $\overline{Z \cap S(T)}$ denotes the average value of shadow regions in Z. $\overline{Z \cap S^C(T)}$ denotes the average value of the non-shadow regions in Z. The difference between them is weighted by a quadratic function G(T), to avoid too high or too low T. The best T should make the mean value of shadow regions and that of non-shadow regions have the biggest weighted difference. The weight α is calculated as:

$$\alpha = e^{\kappa/\eta}$$

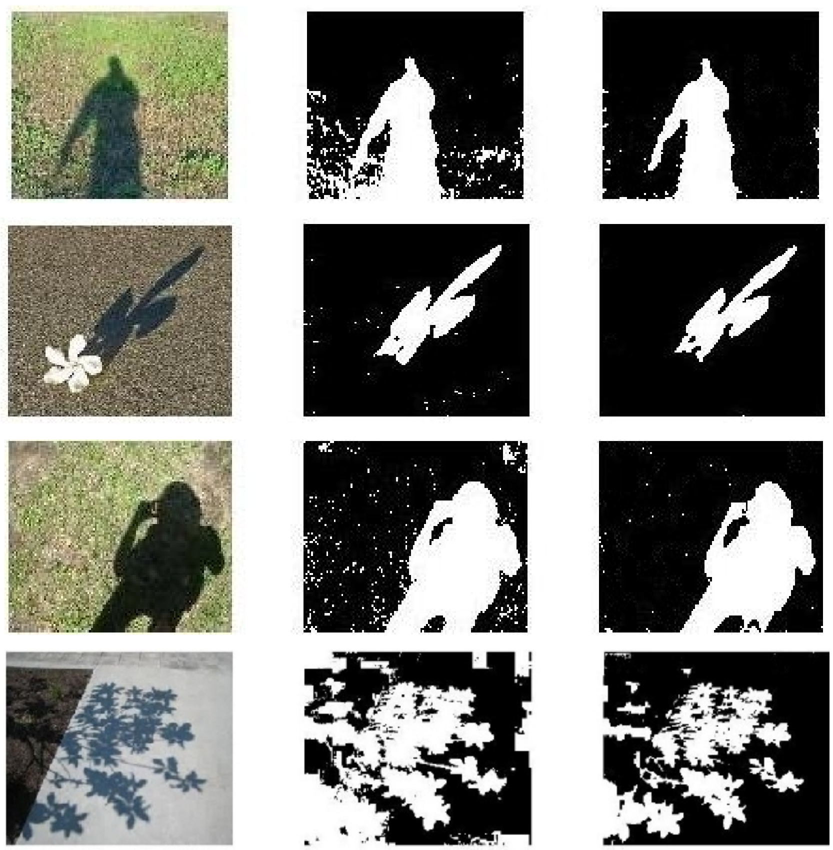
where $\kappa = \frac{\overline{X \cap S^C} - \overline{X \cap S}}{\bar{X}}$ and $\eta = \frac{\overline{Y \cap S^C} - \overline{Y \cap S}}{\bar{Y}}$

α is initialized with $\frac{\bar{Y}}{\bar{X}}$. Repeating the above steps to update T and α until $\zeta(T_{new}) \leq \zeta(T)$. This threshold value T is used for segmenting the shadow region.

The output of the shadow detection algorithm is a is a binary bitmap called 'shadow mask' where pixel value one corresponds to shadow region and zero corresponds to non shadow region.

5. RESULTS AND DISCUSSION

In this paper a shadow detection method is proposed by combining intensity image and the contrast enhanced TAM image. This method was implemented in Matlab.



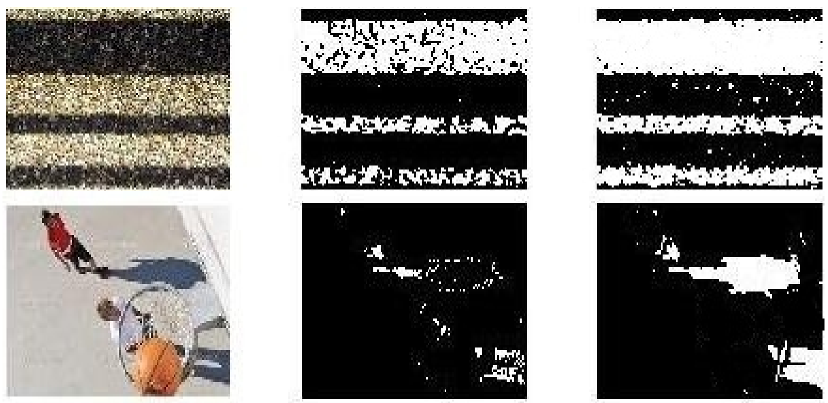
(a) (b) (c)

Fig. 7. (a) Input image (b) Result without contrast enhancement (c) Result using contrast enhancement (AHE)

Enhancing the contrast of the TAM image has made a significant improvement in the shadow detection results. Fig. 7 (a) shows the original input image, of which the shadow has to be detected. Fig. 7 (b) shows the resulting shadow mask without using any contrast enhancement on TAM image. Fig. 7 (c) shows the shadow mask after enhancing the contrast of the TAM image.

Histogram equalization is the widely used technique for contrast enhancement in digital images. But the ordinary histogram equalization is suitable only when the pixel intensities are evenly distributed throughout the image. But the images given as the input to our shadow detection system usually contain regions of the accumulated dark pixels due to the presence of shadows. Hence we used AHE instead of ordinary histogram equalization. In AHE each pixel is transformed based on the histogram derived from its neighbourhood region. Therefore it is suitable for enhancing the local contrast of an image.

Fig. 8 (a) shows the input image given to the shadow detection system. Fig. 8 (b) shows the detected shadow region which is obtained by combining TAM image enhanced with ordinary histogram equalization and the intensity image. Fig. 8 (c) shows the detected shadow region obtained by combining TAM image enhanced with AHE, and the intensity image.



(a) (b) (c)

Fig. 8. (a) Input image (b) Using histogram equalization (c) Using AHE

6. CONCLUSIONS

Detection and removal of shadows in still images enhances many computer vision applications. The effectiveness of a shadow removal algorithm relies on the accuracy of the shadow detection result. In this paper a methodology for shadow detection is proposed by enhancing the TAM image using adaptive histogram equalization. This improves the contrast of the TAM image and thereby improving the quality of detection results. Combining TAM and intensity image avoids the need for segmentation. Furthermore, it requires only one threshold for detecting shadows. These advantages make this method easier to use and more robust in applications. Different still images with shadows were tested and verified.

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