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New spectrum ratio properties and features for shadow detection

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ABSTRACT

Successfully detecting shadows in still images is challenging yet has wide applications. Shadow properties and features are very important for shadow detection and processing. The aim of this work is to find some new physical properties of shadows and use them as shadow features to design an effective shadow detection method for outdoor color images. We observe that although the spectral power distribution (SPD) of daylight and that of skylight are quite different, in each channel, the spectrum ratio of the point-wise product of daylight SPD with sRGB color matching functions (CMFs) to the point-wise product of skylight SPD with sRGB CMFs roughly approximates a constant. This further leads to that the ratios of linear sRGB pixel values of surfaces illuminated by daylight (in non-shadow regions) to those illuminated by skylight (in shadow regions) equal to a constant in each channel. Following this observation, we calculated the spectrum ratios under various Sun angles and further found out four new shadow properties. With these properties as shadow features, we developed a simple shadow detection method to quickly locate shadows in single still images. In our method, we classify an edge as a shadow or non-shadow edge by verifying whether the pixel values on both sides of the Canny edges satisfy the three shadow verification criteria derived from the shadow properties. Extensive experiments and comparison show that our method outperforms state-of-the-art shadow detection methods.

1. Introduction

Shadows are physical phenomena observed in most natural scenes. Recently, shadow detection has attracted a lot of attention in computer vision and pattern recognition communities. Shadows in an image can provide useful information about the scene. For example, they provide cues about the location of the Sun as well as the shape and the geometry of the occluder. Lalonde et al. [1] employed detected shadows to estimate the most likely illumination direction in outdoor scenes. Cao and Hassan [2] employed multiple views of objects and their cast shadows to perform camera calibration. Kawasaki and Furukawa [3] proposed a method to reconstruct 3D scenes using cast shadows and scene geometries. On the other hand, removing shadows in an image significantly aids in a wide range of important computer vision tasks, such as feature extraction, image segmentation, object detection, and object tracking. Based on shadow detection methods, some shadow removal methods (like [4–7]) can be applied to remove the detected shadows. No matter utilizing or removing shadow, it should be detected first. Therefore, shadow detection is of great practical significance in computer vision and pattern recognition.

For shadow detection on images, a high proportion of shadow detection methods focus on detecting moving shadows [8–14]. Moving shadow detection methods firstly employ the frame difference technique to locate moving objects and their moving shadows. The problem of shadow detection then becomes differentiating the moving objects from the moving shadows. Recently, learning approaches are commonly applied in the shadow detection literature. The representative learning approaches include the Gaussian mixture model [15] for learning the background appearance variations under cast shadow, the unsupervised kernel-based model [16] for estimating the cast shadow direction, and the Support Vector technique for co-training different shadow features [17]. Interested readers may refer to [18,19] for a good review of shadow detection methods in video sequences. However, these successful moving shadow detection methods cannot be applied to detect static shadows in a single image.

Compared with detecting moving shadows, detecting static shadows is a more challenging task. It can be applied in a larger variety of applications and has recently been attracting more attentions in computer vision and pattern recognition. Some static

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shadow detection methods require two images to provide complementary information for a more accurate shadow detection. Finlayson et al. [20] employed a chromogenic camera to take two pictures of a scene to detect shadows. Iwama et al. [21] proposed a calibrated binocular camera-based method to segment shadows. As a special application of detecting shadow in single images, some literatures [22–24] focus on detecting shadows in aerial images. Very recently, learning approaches have been extended from moving shadow detection to static shadow detection. Lalonde et al. [25] proposed a conditional random field learning approach to detect ground shadows in consumer-grade photographs. Zhu et al. [26] combined boosted decision tree and conditional random field learning to detect shadows in monochromatic images. Guo et al. [27] trained their classifier using SVM with the RBF kernel to detect shadows for a single image. Panagopoulos et al. [28] employed the Fisher distribution learning method to model shadows with 3D geometry information as prior knowledge. The performance of these learning-based methods often depends on the training sets. In other words, learning on different training sets may lead to different shadow detection results. Furthermore, these learning-based methods may be time-consuming since they often need to extract complex statistical features, e.g., texture and histogram, to feed into the classifier for detecting shadows. As a result, they may not be applicable in real-time applications.

Despite these extensive studies, robust static shadow detection remains a difficult problem. To a large extent, it is due to the lack of robust shadow features. The most straightforward feature of a shadow is that it darkens the surface it casts on. This feature is adopted by some methods directly [23] or indirectly [12]. Other features like histograms [29], texture [30], color ratio [31], and gradient [32] are also frequently adopted. These features may not be robust enough in some applications. For example, shadowed regions are often dark, with less texture and little gradient, but some non-shadowed regions may also have similar characteristics. Therefore, new shadow properties and features are important to perform shadow detection and processing.

As a nature phenomenon, a shadow has physical properties that should be adopted in shadow detection. As illustrated in Fig. 1, humans may identify a shadow by exploring the contrast near edges. Without contrast, it is difficult to determine whether the color checker is in the shadow or not. Therefore, the contrast between the shadow and its background should be used to perform the shadow detection task. In our previous work [33], we proposed the tricolor attenuation model that describes the attenuation relationship between a shadow and its non-shadow background in three color channels. In our follow-up work [34], we further deduced a linear model that describes the pixel values of surfaces in a shadow region and a non-shadow region have a linear relationship. The aim of this work is to find additional new physical properties of shadows by analyzing the sRGB color matching functions (CMFs) and spectral power distribution (SPD) of illumination, and then take these shadow properties as features to design a novel and effective shadow detection method. The contributions of this paper include:

- We observe that in each color channel the point-wise product of daylight SPD with CMFs (H=R, G, B) roughly approximates to the point-wise product of skylight SPD with CMFs (H=R, G, B) multiplying a constant (we name it as spectrum ratio). We further show that the ratio of pixel values of a surface illuminated by daylight vs. those by skylight equals to the constant, which is independent of surface reflectance and holds true in each of the three color channels.
- Based on the calculated spectrum ratios under various representative Sun angles, we found out four new shadow properties which represent physical characteristics of shadows.
- Following the four new shadow properties, we derive three verification criteria and then propose an effective shadow detection method which can quickly locate shadows.

The rest of the paper is organized as follows. In Section 2, we describe the deduced spectrum ratio properties of shadows. In Section 3, we describe the shadow detection method. In Section 4,

Fig. 1. Illustration of non-obvious and obvious shadows. It is much easier for us to identify shadows by exploring the contrast near edges. The two checkerboards shown in (a) were captured under identical imaging environment with the two pictures shown in (b).

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