Shadow Detection and Removal in Still Images by using Hue Properties of Color Space and Thresholding

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Abstract— This paper involves the review of the Shadow Detection and Removal in still images. No prior information has been used such as background images etc. for finding the shadows. It is a very challenging issue for the computer vision system that shadows effect the perception of artificial intelligence based machines in appropriately detecting the particular object as shadows also picked by them and detected as false positive objects. Also in surveillance, it affects the proper tracking of humans such as at airports. We proposed a method to remove shadows which eliminates the shadow much better than existed methods. RGB space has been used of the images and some morphological operations also applied to get better results.

Key words: Shadow Detection, Color Space, Thresholding

I. INTRODUCTION

The shadows are sometimes helpful for providing useful information about objects.

However, they cause problems in computer vision applications, such as segmentation, detection of the object and counting of the object. Thus shadow detection and removal is a pre-processing task in many computer vision applications [1]. Shadows can either aid or confound scene interpretation, depending on whether we model the shadows or ignore them. If we can detect shadows, we can better localize objects, infer object shape, and ultimate where objects contact the ground. Detected shadows also provide cues for illumination conditions [3] and scene geometry [4]. But, if we ignore shadows, spurious edges on the bound arias of shadows and confusion between albedo and shading can lead to visual processing mistakes. For these reasons, shadow detection has long been considered a scene interpretation's crucial component (e.g., [5], [6]). Yet despite its importance and long tradition, shadow detection remains an extremely challenging problem, particularly from a single image. The main difficulty is due to the complex interactions of geometry, albedo, and illumination.

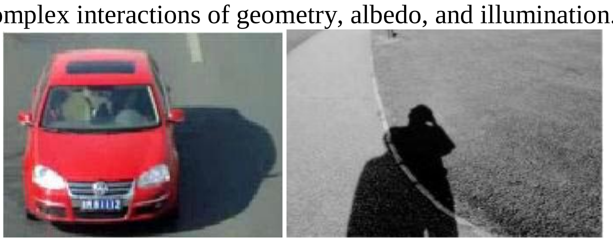

Fig. 1: Different kinds of shadows in image: (a) an overview of different kinds of shadows in one image, (b) cast shadow in a natural scene image [2].

A. Why Cast shadows need to remove?

Many computer vision applications dealing with video require detecting and tracking moving objects. When the objects of interest have a clear cut and well-defined shape, template comparing or more sophisticated classifiers can be used to directly segment the objects from the image. These methods work well for well-defined objects such as vehicles but are difficult to implement for non-rigid objects such as human bodies. A more common approach for detecting people in a video sequence is to detect foreground pixels, for example via Gaussian mixture models [7, 8]. However, current techniques typically have one major disadvantage: shadows tend to be classified as part of the foreground. This happens because shadows measure the same movement patterns and have a similar magnitude of intensity change as that of the foreground objects [9]. Since cast shadows can be as big as the actual objects, their improper classification as foreground results in inaccurate detection and decreases tracking performance. Example schemes where detection and tracking performance are affected include: **(i)** several people are merged together because of their cast shadows; **(ii)** the inclusion of shadow pixels decreases the reliability of the appearance model for each person, expanding the likelihood of tracking loss. Both schemes are illustrated in Figure 1. As such, removing shadows has become an unavoidable step in the implementation of robust tracking systems [10].

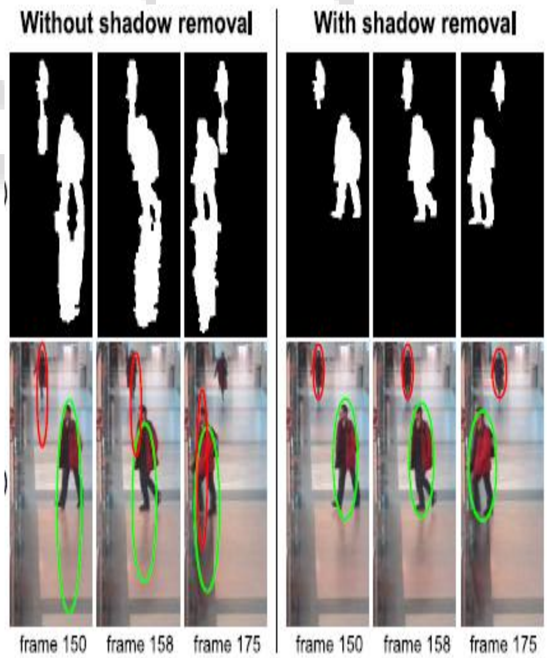

Fig. 2 (a, b): tracking trajectory in a video with and without shadow removal.

B. Overview of shadow information

In real-world scenes a detailed model of shadow formation needs to take into account a number of distinct factors, related to the caster, light source and screen:

1) *Caster information:*
   – The format or shape and size of the caster determine size and shape of shadow.

- The position (and pose) of the caster, particularly with respect to the light source, affects the format, size and location of the shadow;
- Opaque objects cast solid shadows, but translucent objects cast colored or weak shadows.
- Light information:
- The format and size of the light source determine characteristics of the penumbra.
- The position of the source (along with the position of the caster) determines location of the shadow.
- Light source intensity determines the variation between shaded and non-shaded areas.
- The intensity or excess of any ambient illumination also affects contrast.
- The color of ambient illumination determines the color of the shadow.
- Screen information:
- Screen location with regard to light source determines the degree of distortion in shadow shape.
- The shape and location of background clutter can cause shadows to split, distort, or merge.

II. LITERATURE REVIEW

Below is an overview of some existed techniques in shadow detection which helps us in understanding the problem of shadows.

A. Prati et al [11] conducted a survey on detecting moving shadows; algorithms dealing with shadows are classified in a two-layer taxonomy by the authors and four representative algorithms are characterized in detail. The first layer classification considers whether the decision process introduces and exploits uncertainty. Deterministic methods use an on/off decision process, whereas statistical methods use probabilistic functions to describe the class membership. As the parameter selection is a difficult problem for statistical methods, the authors further spited statistical methods into parametric and nonparametric methods. For deterministic approaches, algorithms are classified by whether or not the decision can be supported by model-based knowledge. Horprasert et al's method [12] is an example of the statistical nonparametric method and the authors denote it with symbol **SNP**. This method exploits color information and uses a trained classify to distinguish between object and shadows. I. Mikic et al [13] proposed a statistical parametric approach (**SP**) and utilized both spatial and local features, which developed the detection performance by imposing spatial constraints.

S. Nadimi and B. Bhanu [14, 15] proposed physical model based method to detect moving shadows in video. They used a multistage method where each stage of the algorithm removes moving object pixels with the physical model's knowledge. Input Shadow Detection and Removal in Real Images: A Survey video frame is passed through the system consists of a moving object detection stage followed by a series of classifies, which differentiate object pixels from shadow pixels and remove them in the candidate shadow mask. At the end of the rearmost stage, moving shadow mask as well as moving object mask is accomplished. Experimental results demonstrated that their approach is robust to widely different background surface, illumination conditions and foreground materials.

In monochromatic images, Zhu et al. [17] classify regions based on statistics of intensity, texture and gradient, computed over local neighborhoods, and refine shadow labels using a conditional random field (CRF). Lalonde et al. [16] find shadow boundaries by comparing the color and texture of neighboring regions and employing a CRF to encourage boundary continuity. Panagopoulos et al. [18] jointly infer global illumination and cast shadow when the coarse 3D geometry is known, using a high-order MRF that has nodes for image pixels and one node to represent illumination. Recently, Kwatra et al. [19] proposed an information theoretic-based approach to detect and remove shadows and applied it to aerial images as an enhanced step for image mapping systems such as Google Earth.

After detecting shadows, we can apply the matting technique of Levin et al. [20], treating shadow pixels as foreground and non-shadow pixels as background. By using the recovered shadow coefficients, we can calculate the ratio between direct light and environment light and generate the recovered image by relighting each pixel with both direct light and environment light. To take measure of our shadow detection and removal, we will use pictures from previous papers as well as our own.

III. PRESENTED METHOD

Shadows can be detected using the features extracted from three domains: spectral [21] spatial [22] and temporal [23]. Nevertheless, temporal features are not very reliable because they depend heavily on the object speed and the frame rate of the camera. Hence, this paper mainly focuses on spectral and spatial features. Particularly, the following characteristics are exploited to detect shadow:

- Chromaticity: when there is shadow, object chromaticity remains the same.
- Texture: alike, shadows could only slightly change object texture.
- Intensity reduction: for a specific or rigid scene and a specific lighting configuration, shadows could not reduce too much object luminance.

Our proposed method used chromaticity hue domain for detection and removal of shadows.

Below are the steps for shadow detection and removal system

- Step 1) Load images having shadows in it in matlab work space.
- Step 2) Convert RGB color space to one dimensional chromaticities of red and blue channel with respect to geometric mean. Chromaticities can be represented using the standard RGB color space .In RGB color space, chromaticities are represented by two values r and g:r = R/R + G + Band g = G/R + G + B where R,G,B is the intensity level of red, green, blue in RGB color space. Because these values are independent, a small chromaticity change provokes a small change of r or g or both of them.
- Step 3) the next step is to find log-chromaticity for r and g obtained above. The log-chromaticity space (LCS) is a color space with excellent illumination-

invariant properties. When converting RGB colors to LCS, there exist different options for choosing the normalizing channel. Based on synthetic and real image data we find that the geometric mean does not introduce a bias to the color clusters and always results in an intermediate clustering performance.

- Step 4) in this step, An illumination direction for each respective color set is determined in the logarithmic graph that is orthogonal to the non-linear illumination-invariant kernel. A log-chromaticity value of each plotted pixel is projected on the non-linear illumination-invariant kernel. This results in reduction of the shading region in the image
- Step 5) after this, threshold methods has been applied to detect the shadow region and removal of shadow.

IV. RESULTS AND DISCUSSIONS

Experimental results have been carried out on number of images. Below are results at different stages of the algorithm.

Fig. 3: test image

Fig. 4: resulted image with shadow removal

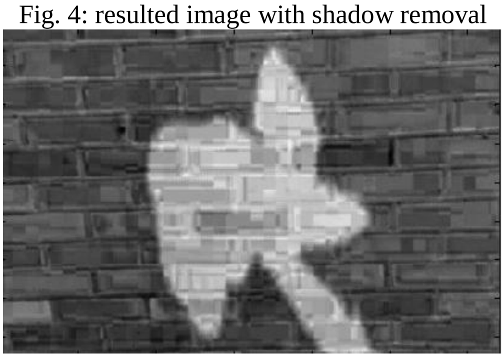

Fig. 5: Shadow area marked as high intensity values and non-shadow as low intensity values

It has been found that mean value of the resulted image has been increased from .4258 to .48 and average gradient has been increased from .0103 to .0233. This increase in average gradient results from removal of shaded regions in image and hence texture left on that area have pixels of varying intensities.

V. CONCLUSION

Method has been applied on number of images. From results it has been concluded that algorithm works well on natural scene images but give poor results on closed scenes. Also its output is in gray scale. In future, algorithm can be modified to improve efficiency in closed camera scenes and it should be modified to bring the resulted output in colored images.

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