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Shadow Detection in Single Image using Color Spaces

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Abstract: A shadow basically is a sort of image produced when light is blocked. A shadow generally takes up most of the space behind an opaque item with light right in front of it. Shadows often introduce errors in the performance of computer vision algorithms, such as object detection and tracking. For better performance, there is need to detect shadow from image and remove it to get shadow free image. This paper proposes a simple method to detect shadow from images. In this paper LAB color space is used to detect shadow. Here L means lightness, A and B are two different color dimensions. Working with the Lab color space includes all of colors in the spectrum, as well as colors outside of human perception. This paper discusses all the steps to be carried out in achieving the desired objective i.e to detect the shadow from image by using some simple steps.

Keywords: Shadow detection, shadow removal, LAB color space, illumination.

I. INTRODUCTION

Shadows in images create lots of problems on image analysis. There is no need of shadow in an image i.e. shadow is unwanted part in images. Shadow affects the images because of shadow lots of data and information is lost from images.

The presence of shadows has been responsible for reducing the reliability of many computer vision algorithms, including segmentation, object detection, scene analysis, stereo, tracking, etc. Therefore, shadow detection and removal is an important pre-processing for improving performance of such vision tasks.

Decomposition of a single image into a shadow image and a shadow-free image is a difficult problem, due to complex interactions of geometry, albedo and illumination. Many techniques have been proposed over the years, but shadow detection still remains an extremely challenging problem, particularly from a single image. Most research is focused on modeling the differences in color, intensity, and texture of neighboring pixels or regions. To determine if a region is in shadow, we must compare the region to others that have the same material and orientation. For this reason, most research focuses on modeling the differences in color, intensity, and texture of neighboring pixels or regions.

1.1 The Appearance of Shadows

In a local shading model, shadows occur when the patch cannot see one or more sources. In this model, point sources produce a series of shadows with crisp boundaries; shadow regions where no source can be seen are particularly dark. Shadows cast with a single source can be crisp and black depending on the size of the source and the albedo of other nearby surfaces (which could reflect light into the shadow and soften its boundary) [8]. The geometry of the shadow cast by a point source on a plane is analogous to the geometry of viewing in a perspective camera (Figure 1.1).

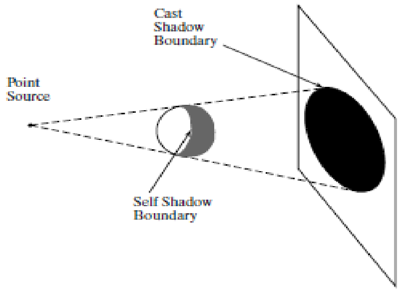

FIGURE 1.1:Self-shadow, cast shadow taking light source as point source

Any patch on the plane is in shadow if a ray from the patch to the source passes through an object. This means that there are two kinds of shadow boundary. At *self shadow boundaries*, the surface is turning away from the light, and a ray from the patch to the source is tangent to the surface. At *cast shadow boundaries*, from the perspective of the patch, the source suddenly disappears behind an occluding object. Shadows cast onto curved surfaces can have extremely complex geometries, however. If there are many sources, the shadows are less dark (except at points where no source is visible), and there can be many qualitatively distinct shadow regions (each source casts its own shadow—some points may not see more than one source).

II. RELATED WORK

A lot of work has already been done in this field and there is a scope of lot more as well. A brief review is presented as follows:

The method based on color space shadow elimination algorithm considers that the value of the shadow pixels are

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linearly attenuated comparing with the corresponding background pixels. This linear attenuation property has been employed in different colors spaces like RGB [5], HSV [1], and YUV [4].

In [5], the proposed algorithm users consider that cast shadow reduces surface brightness and saturation while maintaining chromaticity properties in the RGB color space. [1] Explores color differences between shadow and the corresponding background pixels in different color space.

Cucchiara et al. [6] first defined an approach of shadow detection based on HSV color space. They assume that the HSV component is smaller than it's priori value when shadowed.

The author in [6] adopts the YUV color space to avoid using the time consuming HSV color transformation. They were able to segment shadows and foreground objects following their observation that shadows reduced the pixel value linearly to its prior value in the YUV space. These methods can split part of the shadow pixels, but when the pixel's color similar with the background pixel that it can't segment the shadow pixels. The method based on statistical information shadow removal algorithm considers that the pixel can divide to cast shadows, and model their generation and then learning the large samples.

YAN Jinfeng et al. [3] proposes an approach based on regional growth to detect moving cast shadow. Firstly, the pixel distribution histogram in RGB color space or the luminance ratios in HSV color space is used to detect the possible shadow area, which can produce a possible shadow area to reduce the calculation of subsequent processing. Secondly, we implement the regional growth approach based on the Breadth-First Search algorithm to get a relatively accurate shadow area. This approach considers both the color information and the edge features of images, which yields accurate detection of moving cast shadows as shown by experiments.

Lalonde et al. [4] find shadow boundaries by comparing the color and texture of neighboring regions and employing a CRF to encourage boundary continuity.

Panagopoulos et al. [2] 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.

III.PROPOSED METHODOLOGY

STEPS TO BE INVOLVED IN THE THESIS:

Step 1) Conversion of RGB color space to Lab color space

To detect shadow initially the RGB image is converted to an LAB equivalent image. The LAB color space has three channels where L is the Lightness channel, A and B are the two color channels. The L channel has values ranging from 0 up to 100, which corresponds 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 color having more red or yellow and a low value represents a color having more green or blue. 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.

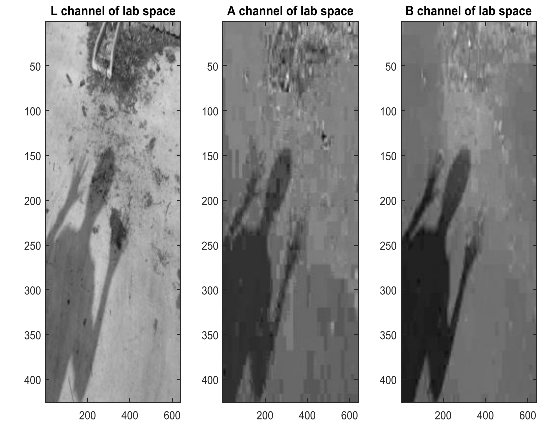

FIGURE 1: (a) L channel (b) A channel
(c) B channel of Lab color space

Step 2) Using mean and standard deviation of different channels to classify image into shadow and non-shadow region

Then the mean values of the pixels in L, A and B planes of the image have to be computed separately. Now if mean (A) + mean (B) ≤ 256, then the pixels with a value in L ≤ (mean (L) – standard deviation (L)/3) can be classified as shadow pixels and others as non-shadow pixels. Otherwise the pixels with lower values in both L and B planes can be classified as shadow pixels and others as non-shadow pixels [7]. This pixel-based method may classify some non shadow pixels as shadow pixels.

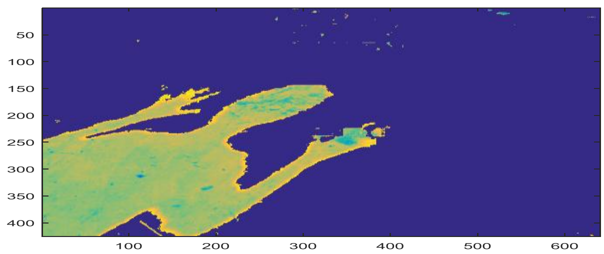

FIGURE 2: Results after threshold using mean and standard deviation

Step 3) Applying morphological operations for final filtering

Cleaning, a morphological operation can remove isolated pixels. 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

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threshold can be considered as shadow regions. All these morphological operations thus help to eliminate misclassification of pixels.

FIGURE 3: Results after filtering process using morphological operations

Step 4) Applying connected component labelling to get the biggest object in the image carrying cast shadow

In this we used bwlabel command for getting the objects according to connectivity and use area property of ‘regionprops’ command to get the biggest area element.

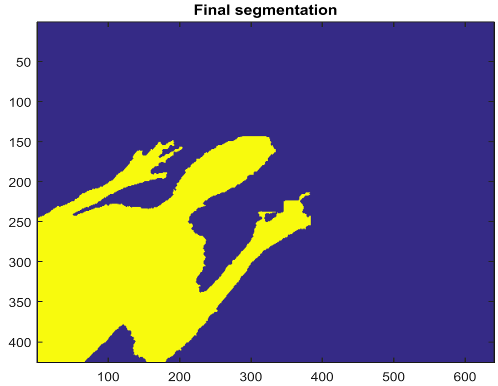

FIGURE 4: Results after connected component labeling

IV. CONCLUSION

The presence of cast shadows in an image can modify the perceived object shape and cause its incorrect segmentation. In this work, we detected the shadows using lab color space. In detection process, we separate shadow pixels from the foreground region. As we know, color space shadow elimination method tends to eliminate the most of shadow effectively, but some parts of foreground are filtered, which results in the distortion of foreground outline simultaneously. The method based on chromaticity can keep the foreground outline well although some foreground pixels will be misclassified as shadows. 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

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