Rgb Color Chromaticity Based Shadow Detection and Reomoval in Cast Images

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Abstract- *In this paper, both shadow detection and shadow removal has been carried out using two different algorithms. In shadow detection, first RGB shadow image is converted to Lab color space then mean and standard deviation has been calculated for all three L*a*b channels individually. Then shadow and non-shadow regions are separated based on threshold parameter. The shadow removal process consists of two stages: detecting the shadow regions and reconstructing a shadow-free image. In this method we are normalizing the image using all the three R, G, B channels which is found to be more efficient than normalizing using any one colour channel. A 2D log chromaticity image is then obtained and by projecting it at an angle, obtained as a result of entropy minimization technique, a 1D illumination invariant image is created. Finally a shadow free illumination invariant chromaticity image is obtained. From the results, the main observation is that the method is relying on the entropy minimization algorithm and the accuracy of the resultant projection angle is one of the important parts for shadow removal. Performance evaluation of shadow detection method has been carried out using sensitivity, specificity and accuracy parameters. Similarly performance evaluation of shadow removal has been carried out using mean of intensity and average gradient in the images.*

Keywords- Standard Deviation, Shadow Detection, Chromaticity Image, shadow removal etc.

I. INTRODUCTION

Shadows in digital images are either helpful or troublesome in image processing and pattern recognition. The shadows in an aerial image provide visible evidence of the existence of objects. The shadows can be used to recognize and track object in video surveillance and estimate the height and/or position of buildings. However, the existence of shadows also causes some undesirable problems. For example, the shadows may cause objects to merge or shapes to distort, thus resulting in information loss or distortion of objects [1]. On one hand, the shadows attached to some detected objects will misclassify the objects and their shadows as a totally erroneous object in the image. On the other hand, the shape distortion makes the segmentation method less reliable. So shadow detection and removal is an important preprocessing step before analysis the remote sensing images. Different types of algorithm have been developed for shadow detection and removal

Shadow detection methods are classified into two types:

- the method based on features,
- the method based on models [2].

1) The method based on features

The first type of shadow detection method, feature-based method, uses the intensity values, chromaticity information, or geometric characteristics to detect the shadows. For example, if the intensity value of a region is lower than that of the pixels around, the region is detected as a shadow region in gray aerial images. Some algorithms have been presented for this kind of images [3]. However, here arises the problem, for some nonshadow regions with low-intensity surface features may be identified as shadows, such as black cars or buildings. Color images are thus introduced in the shadow detection. The chromaticity information in color aerial images is used to improve the shadow detection accuracy. The problems in identifying shadows include boundary ambiguity, color variability, variation of lighting, weather effects, and others. Shadows in aerial images have the following properties: [4]

- Lower luminance (intensity) because the electromagnetic radiation from the sun is blocked.
- Higher saturation with short blue-violet wavelength due to the Rayleigh effect of atmospheric scattering.
- Increased hue values, because the intensity change of a shaded area when compared to an unshaded area is proportional to the wavelength.
- Increased entropy, which denotes the randomness of the pixels in that region.

High resolution aerial images support a wide range of application fields as biomass estimation for energy studies, water analysis for pollution detection, environment and ecology investigations, and urban sprawl assessment.

Although VHR images are capable of providing high precision measurements for classification procedures, they frequently contain cloud and cast shadows that generate problems for the reliable extraction of the needed information. Commonly, shadows cause partial or even total loss of radiometric signature in the investigated area and therefore the process of classification and object detection can be biased or even fail [5]. From the previous considerations, to properly classify images it is mandatory to reduce or remove shadows, and this requires their accurate identification.

II. LITERATURE SURVEY

In this section, a brief survey has been provided about the effective work done in shadow detection and removal area

Jie Li et. al. [6] identified the intensity property, chromaticity property of the shadow areas, and the color attenuation relationship derived from Planck's blackbody irradiance law are used iteratively to segment each candidate region into smaller sub-regions, so that whether each sub-region is true shadow region. The extracted hue singularity pixels are classified on the base of its neighboring pixels. From the experimental results, it could be concluded that their proposed shadow detection algorithm presents best shadow detection accuracy when compared with Tsai's and Chung et al.'s algorithms.

Xiaojun Qi et. al. [7] proposed a novel shadow detection algorithm for still images. Their method can effectively extract shadows from a single image with complex outdoor scenes without requiring any prior knowledge. Compared with the state-of-the-art learning-based methods employing a complex classifier to learn several complicated shadow features, their method only requires a simple verification on Canny edges. Such a simple algorithm achieves better shadow detection results in a shorter time, indicating the effectiveness of the proposed spectrum ratio properties. These advantages may make their algorithm easier to use in practical applications.

Grace B. Carneiro et. al. [8] implemented and tested their algorithms in three different aerial real scenes, obtained in different flights and locations, at different times, with different scene complexities and different illumination conditions. They started with the aerial images in RGB format and mapped them into CIELCh space. They then calculated the Specthem Ratio images which highlighted the low luminance areas. Then they applied multilevel thresholding to obtain raw masks. After that they applied morphology operations to preserve the shapes of the masks and reduce noise, obtaining the final shadow masks. At last they used the masks to perform local processing in shadow regions, using the statistical information of their (unshaded) boundaries to relight the shaded pixels.

Peng Qi et. al. [9] proposed a method to detect unwanted shadow areas from moving objects. The proposed technique exploits three- dimensional location information properties of shadows in a scene to perform this task. The proposed method is robust against complex, dynamic backgrounds. The contribution offers a shadow detection method from a new perspective and contribution to tracking and stereo matching fields. Traditional 2D tracking can be expanded to 3D positioning and tracking. Stereo matching in the same plane will become easier.

A. Movia et. al. [10] developed an improved algorithm for automatically detecting shadows in VHR aerial images, based only on the RGB bands without NIR information. Further, two novel transformation models derived from Procrustes analysis, having the ability to directly estimate coordinate transformations between point configurations that are indefinitely rotated, translated and scaled, have been proposed for recovering pixels in shadow regions.

Dhanya V et. al. [11] presented a novel algorithm for shadow detection and removal in urban high resolution satellite images. The proposed technique segments the shadow by using tri-class based Thresholding. This segmentation helped to handle a rather difficult problem of shadow detection in satellite imagery. After the segmentation shadow should be detected by using bimodal histogram splitting method. Then the false shadow that is some clutter information is removed for accurately detecting shadow. Also an additional method called pair wise region based detection is used to accurately detect the shadow. Then image is clustered by using K-mean clustering and detected shadow by comparing color and ratio of intensities in the adjacent pair. This method can accurately detect the shadow. Also they develop a new method called soft matting is used for shadow removal. This method can accurately restore the shadowed region. Both qualitative and quantitative experimental results using real images show that the proposed algorithm outperforms a comparable algorithm for shadow detection and removal.

Pablo Barcellos et. al. [12] proposed a new stochastic shadow detection method, designed to overcome the limitations identified in most shadow detection methods. The proposed shadow detection method receives as input the segmented foreground objects and their cast shadows, and outputs the detected shadow regions. It relies on chromatic and gradient information that is integrated with the stochastic hypergraph segmentation of the video frames using a cascade of shadow/non I shadow classifiers. A majority voting scheme is used to detect the shadow regions in the input stream.

III. PRESENT WORK

System module for shadow detection is described in below figure 1.

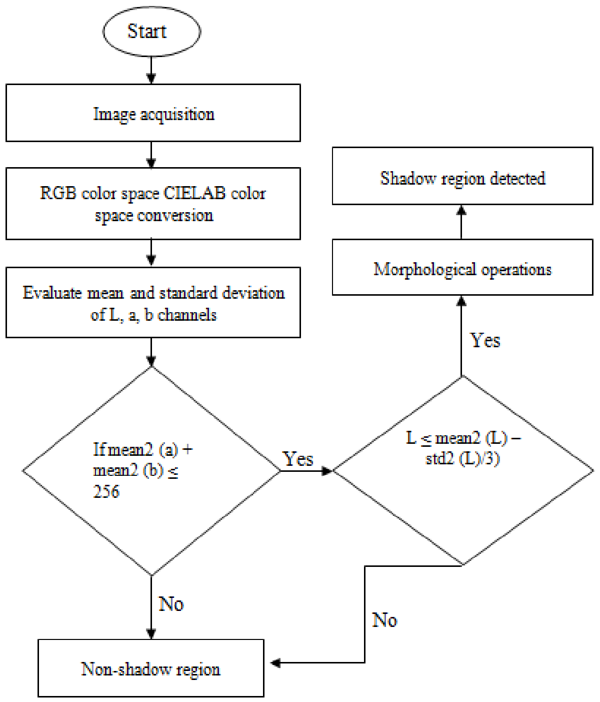

Figure 1: Flowchart for shadow detection algorithm

The steps involved at this step are briefed as below:

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

- The image is generally described in RGB color space. RGB is an acronym for red, green and blue and can produce any chromaticity that is the triangle defined by those primary colors.
- Extracting the characteristic value in gray space is considerable due to the simple and fast algorithm. However, the most used of these is the CIELAB color space due to the uniform distribution of colors, and because it is very close to human perception of color.
- The coordinates of CIELAB color model are denoted by three components: L, a, and b. Component a and b just reflects color information, while L is an acronym for luminosity in CIELAB color space.
- Besides, the CIEXYZ color space needs to be determined. The first step carries out the RGB to CIEXYZ transformation (the RGB components are made linear with Gamma correction).

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

And the second step carries out the CIEXYZ to CIELAB transformation

$$L = \begin{cases} 116\left(\frac{Y}{Yn}\right)^{1/3} - 16 & \frac{Y}{Yn} > 0.01 \\ 903.3\left(\frac{Y}{Y_n}\right), & \frac{Y}{Y_n} \le 0.01 \end{cases} \quad \ldots\ldots\ldots\ldots\ldots (2)$$

$$a = 500\left[\left(\frac{X}{X_n}\right)^{1/3} - \left(\frac{Y}{Y_n}\right)^{1/3}\right], \quad \ldots\ldots\ldots\ldots (3)$$

$$b = 500\left[\left(\frac{Y}{Y_n}\right)^{1/3} - \left(\frac{Z}{Z_n}\right)^{1/3}\right], \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

where $X_n = 95.07$, $Y_n = 100.00$, and $Z_n = 108.81$ are the valued according to the reference blank of D65 standard illuminant.

Step 2) Evaluation of mean and standard deviation of lab channels

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 [13]. This pixel-based method may classify some non-shadow pixels as shadow pixels.

Step 3) Dilation and erosion as post processing to get the effective shadow pixels

In this step, dilation and erosion operations have been implemented to get the effective shadow pixels in the image.

Finally connected component analysis has been carried out to get the biggest object in the image. This reduces local noise patches in the image which are mis-classified as shadow pixels

IV. RESULTS AND DISCUSSIONS

The presented algorithm has been applied on number of images having different backgrounds taken from different cameras.

Below is the performance evaluation using sensitivity, specificity and accuracy parameters

Table 1: performance evaluation using sensitivity, specificity and accuracy parameters

Cast Shadow image	Shadow region detected	Specificity	Sensitivity	Accuracy
		1.000	0.7427	0.8713
		0.9842	0.9165	0.9504
		0.9998	0.9591	0.9795
		1.000	0.7767	0.8883

Below are the bar graphs for the evaluated results

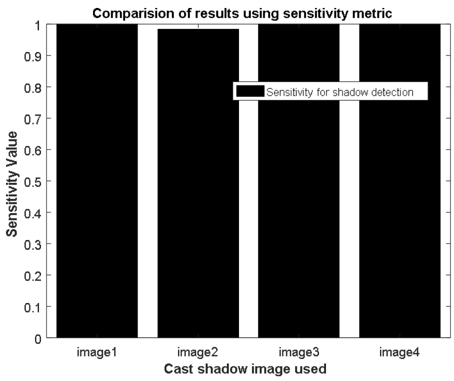

Figure 2: Comparison of results for shadow detected region using sensitivity parameter

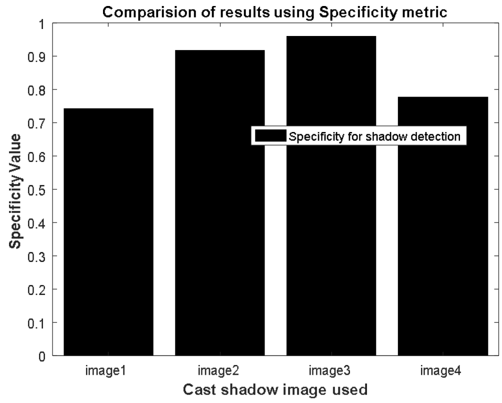

Figure 3: Comparison of results for shadow detected region using specificity parameter

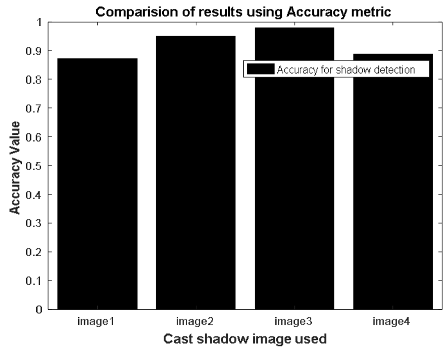

Figure 4: Comparison of results for shadow detected region using accuracy parameter

Similarly results for shadow removal in gray scale images are shown below

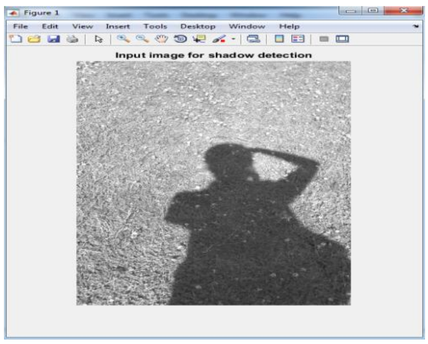

Figure 5: Original picture of grass surface foundation

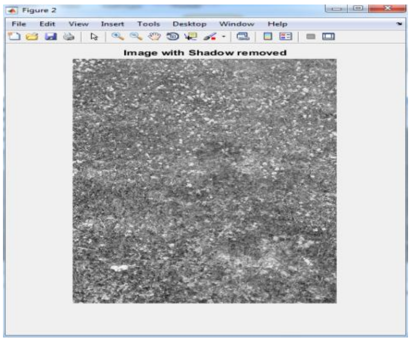

Figure 6: Resulted output after shadow removal.

In this work, in order to objective evaluate the performance of shadow removal system, the statistical parameters were compared using information mean and average gradient. Average gradient can express the ability of small details and can be used to evaluate the clarity of the image, the greater its value, the more clear that the image. In addition, to some extent, the mean can be used to evaluate the image contrast. Below is the table 2 which shows mean and average gradient of the image.

Table 2: Mean and Average Gradient with and without shadow removal for image one.

Image Type	Mean	Average Gradient
With shadow	0.5774	0.0428
Shadow removal	0.5777	0.0979

From the table increased values of mean and average gradient shows the decrease in overall contrast area due to shadow removal in the image

So also comes about for different pictures are demonstrated as follows

V. CONCLUSION

There are multi-illuminants in most real-world environments. Shadows are cast when an object lies in the way of the main illuminant. Therefore, not only the intensity but also the chromaticity of shadow regions and non-shadow regions are different. The presence of shadows in an image has been a problem for a variety of computer vision tasks such as image segmentation, object recognition and tracking. Thus, being able to remove shadows could improve the performance of these tasks. To explore this problem we have proposed a shadow detection model based on L*a*b color space. First Evaluation of mean and standard deviation of lab channels has been carried out. Then the mean values of the pixels in L, A and B planes of the image have to be computed separately. if mean (A) + mean (B) is less than or equal to a chosen threshold, 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. This pixel-based method may classify some non-shadow pixels as shadow pixels. To improve this, morphological operations and connected component analysis has been used to filter out the most effective shadow pixels in the image. Experimental results show high accuracy of true detection of shadow regions in the image. Then shadow removal has been carried out based on 2D log chromaticity defined as R/G and B/G of red and blue channels with respect to Green channel. A 2D log chromaticity image is then obtained and by projecting it at an angle, obtained as a result of entropy minimization technique, a 1D illumination invariant image is created. Finally a shadow free illumination invariant chromaticity image is obtained. From the results, the main observation is that the method is relying on the entropy minimization algorithm and the accuracy of the resultant projection angle is one of the important part for shadow removal.

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