Paired Region Approach based Shadow Detection and Removal

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Abstract—Shadow detection and removal in various real life scenarios including surveillance system, indoor outdoor scenes, and computer vision system remained a challenging task. Shadow in traffic surveillance system may misclassify the actual object, reducing the system performance. However, shadow causes problems in computer vision applications such as segmentation, object detection and object counting. That's why shadow detection and removal is a pre-processing task in many computer vision applications. So we propose a simple method to detect and remove shadows from a single natural scene image. The proposed method begins by selecting natural scene image and by segmenting method we focus only on shadow part. In image classification, we distinguish between the shadow and non shadow pixels. So that we able to label shadow and non shadow regions of the image. Once shadow is detected that detection results are later refined by image matting and the shadow-free image is recovered by removing shadow region. Examination of number of examples indicates that this method yields a significant improvement over the previous methods.

IndexTerms—Shadow detection, segmentation, region classification, shadow removal, matting.

I. INTRODUCTION

Shadows in images have long been disruptive to computer vision algorithms. They appear as surface features, when in fact they are caused by the interaction between light and objects. This may lead to problems in scene understanding, object segmentation, tracking and recognition. Because of the undesirable effects of shadows on image analysis, much attention was paid to the area of shadow removal over the past decades and covered many specific applications such as traffic surveillance, face recognition, image segmentation and so on[2] [3] [4]. A shadow occurs when an object partially or totally occludes direct light from a source of illumination. Shadows can be divided into two sets: self shadows and cast shadows. A self shadow occurs in the portion of an object whereas a cast shadow is the dark area projected by the object. Cast shadows can be further classified into umbra and penumbra region, which is a result of multi-lighting. One crucial difference between these shadows is their contrast to the background. Usually, self shadows are vague shadows which gradually change intensity and have no clear boundaries. Cast shadows are, hard shadows with sharp shadow boundaries.

When the light energy is illuminated on the object there the shadow of that object appears. Detection and reconstruction of shadow areas plays a vital role in the image processing environment. The shadow and non-shadow regions are identified only when the light energy is fallen on the object. If the light energy is fallen less that area is represented as shadow region whereas if the light energy is emitted more, this area is represented as non-shadow region. To separate shadow and non-shadow regions here we are implementing image classification process. This complete process depends on the borders extraction. Shadow detection plays a vital role in digital aerial image processing. Shadows are useful information that can be used in building location recognition, 3-D restoration and height estimation. Shadow can provide semantic and geometric information about the height and shape of its object and the position of the illumination light. The poor visibility in shadow region influences computer operation such as change detection, scene matching, object recognition and true orthophoto generation. Hence shadows need to be properly detected and remove for image interpretation. Yet despite its importance and long tradition, shadow detection remains an extremely challenging problem, particular from a single image.

Our goal is to detect shadows and remove them from the images. So existing methodology determine whether a particular region is shadowed or not by comparing it to other regions in the image that are likely to be of the same material. To start, it finds pairs of regions that are likely to correspond to the same material and determine whether they have the same illumination conditions. We incorporate these pair-wise relationships, together with region-based appearance features, in a shadow/ non-shadow graph. a sparse set of edge potentials indicate whether two regions from the same surface are likely to be of the same or different illumination. Finally, the regions are jointly classified as shadow/non-shadow using graph-cut inference. But this technique gave only 50% accuracy. So develop proposed methodology which leads to good performance on consumer-quality photographs. Our shadow detection provides binary pixel labels, but shadows are not truly binary. Illumination often changes gradually across shadow boundaries. We also want to estimate a soft mask of shadow coefficients which indicate the darkness of the shadow and to recover a shadow-free image that depicts the scene under uniform illumination. Specifically after detecting shadows, output of preprocessing phase on which we apply the matting technique of Levin et al. [5], treating shadow pixels as foreground and nonshadow pixels as background. Using surrounding non-shadow pixel, that is lighting pixel recovered shadow region. For reconstructing the image we have to go through some phases like classification, masking, matting etc. Finally, we examine the effects of the reconstructed image on the application of classification by comparing the classification maps of images before and after shadow reconstruction.

II. RELATED WORK

A shadow is an area where direct light from a light source cannot reach due to obstruction by an object. There have been few studies concerning shadow removal, and the existing approaches cannot perfectly restore the original background patterns after removing the shadows. Here are our basic assumptions as follows:

- The illumination image is spatially smooth.
- There is no change in the texture inside the shadow region.
- In the shadow regions, the illumination image is close to being constant.

A brief literature review is needed in order to understand work done by various scholars in this field. On the one hand, these shadows may be utilized as a valuable cue for inferring 3-D scene information based on their position and shape, for example, for building detection and building height estimation.[6] On the other hand, existence of shadows may cause serious problems while segmenting and tracking objects: shadows can cause object merging. For this reason, shadow detection is applied to locate the shadow regions and distinguish shadows from foreground objects. In some cases, shadow detection is also exploited to infer geometric properties of the objects causing the shadow ("shape from shadow" approaches). In spite of the different purposes, invariably the algorithms are the same and can extend to any of these applications. There are various approaches proposed by various researchers for shadow detection and removal. In this chapter a brief description of these approaches and comparison between the methods are given.

a) An Object Oriented Shadow Detection and Removal Method

Hongya Zhang et al. [7] put forward an object oriented shadow detection and removal method. In this method, shadow features are taken into consideration during image segmentation and then according to the statistical features of the images, suspected shadows are extracted. Furthermore, some dark objects which could be mistaken for shadows are ruled out according to object properties and spatial relationship between objects. For shadow removal, inner-outer outline profile line (IOOPL) matching is used. First, the IOOPLs are obtained with respect to the boundary lines of shadows. Shadow removal is then performed according to the homogeneous sections attained through IOOPL similarity matching. Here, provided a comprehensive survey of shadow detection and removal in indoor and outdoor scene, traffic surveillance images etc. survey is done on various types of images real time application or traffic images.

b) An Object Tracking Method

Huazhong et al. [8] present a novel method for object tracking in surveillance scenes. There are three components of object tracking process according to the time sequence of object detection and tracking Bottom-Up process, Top-Down process and combination of both. Bottom-Up process detects the object and associate with the video frame. Top-Down process create model for object and involve incorporating prior information about scenes or object. The combination process improves the accuracy and reduces complexity of object tracking by combining information of detection and tracking. This Object Tracking Method improves the "ViBe" background subtraction algorithm by adding the Scale Invariant Local Ternary Pattern operator "SILTP" so as to detect moving shadow and increase the accuracy of segmentation. An object tracking method based on Compressive Tracking and Kalman filter by using the result of background subtraction is presented, improve the accuracy and robustness of the tracking system in surveillance scenes.

c) Regional Growth to Detect Moving Cast Shadow Approach

YAN Jinfeng et al. [9] 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.

d) Extracting the Object from the Shadows like Object/Shadow Discrimination

Kanouivirach et al. [10] propose and experimentally evaluate a new method for detecting shadows using a simple maximum likelihood formulation based on color information. We first estimate, off line, a joint probability distribution over the difference in the HSV color space between pixels in the current frame and the corresponding pixels in a background model, conditional on whether the pixel is an object pixel or a shadow pixel. Given the learned distribution, at run time, we use the maximum likelihood principle to classify each foreground pixel as either shadow or object. In an experimental evaluation, we find that the method outperforms standard methods on three different real-world video surveillance data sets. We conclude that the proposed shadow detection method would be an extremely effective component in an intelligent video surveillance system.

III. PROPOSED SYSTEM

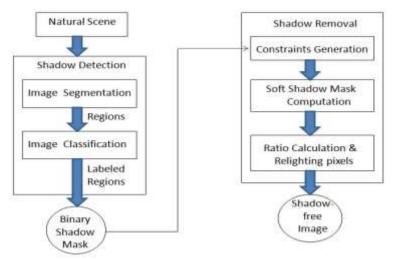


Fig.1 Architecture of Paired Region Approach based Shadow Detection and Removal System

Select Shadow Image:

For our Shadow detection and removal project we are taking image as an input. Select shadow image is a first phase in shadow detection and removal project. Different images are stored in a folder name as images as a database for choosing input for shadow detection and removal.

Segmentation:

This is primary phase of shadow detection system in which the input image is divided into regions by using segmentation. The algorithm for segmentation is mean shift. There are 2 steps in mean shift algorithm: mean shift filtering and mean shift segmentation.

1) Mean Shift Filtering Let xi and zi i = 1, 2...n: d-dimensional input. a. Initialize j=1 and y_i , $x_i = 1$. b. Compute yi+1 according to mean shift vector. j = 1, 2, ...

2) Mean Shift Segmentation

- shift Run the filtering mean procedure for image and store all information about d-dimensional convergence point in
 - $\mathbf{z_i}$ i.e. $\mathbf{z_i} = \mathbf{y_i}$, c.
- b. Identify clusters $\{Cp\}p=1...m$ of convergence points by grouping together all zi which are closer than 0.5 from each other in joint domain.
- c. For each i=1...n

Assign
$$L_i = \{p \mid z_i \in Cp\}$$
.

d. Optional: Eliminate spatial regions smaller than M pixels.

Pair-wise Region Classification:

The presence of shadows in a region cannot be determined by considering only its internal appearance. The region must be compared with other regions with same material. In particular, we want to find same illumination pairs, regions that are of the same material and illumination, and different illumination pairs, regions that are of the same material but different illumination. Differences in illumination can be caused by direct light blocked by other objects or by a difference in surface orientation. In this way, we can account for both shadows and shading. If shadows appear in ambiguous condition then the solution to detect ambiguous appearance of shadows is by paired regions. We train classifiers (SVM with RBF kernel; $C = 1, \sigma = 1$) to detect illumination pairs based on comparisons of their color and texture histograms, the ratio of their intensities, their chromatic alignment, and their distance in the image. These features encode the intuition that regions of the same reflectance share similar texture and color distribution when viewed under the same illumination; when viewed under different illuminations, they tend to have similar texture but differ in color and intensity.

Shadow Removal:

Shadow matting is the removal or extraction of natural shadows from single image. During matting, the foreground elements are extracted from image. For shadow matting, we extract a shadow density map to describe the degree to which each pixel is in shadow.

> Shadow Removal input: binary shadow mask where, each pixel i is assigned k_i value of either 1 or 0 output: shadow-free image Algorithm Given image I, separate foreground image and the background image. Calculate shadow coefficient values for each pixel Generate the constraints for matting. Compute the Soft shadow mask. Recover the shadow-free image.

IV. RESULTS AND DISCUSSION

In our experiments, we evaluate both shadow detection and shadow removal results. For shadow detection, we evaluate how explicitly modeling the pair-wise region relationship affects detection results and how well our detector can generalize cross datasets. Results come at different points of the presented algorithm has been described below:

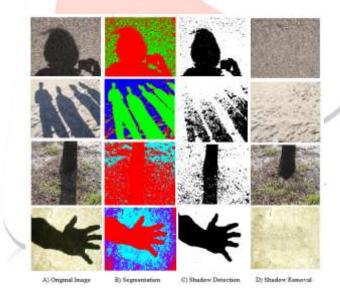


Fig.2 Results

In shadow detection system, input picture will be single characteristic scene which has shadows. The segmentation algorithm will separate given image into regions and after that the classification algorithm arranges these segmented regions. Regions are classified as shadow region and non-shadow region. For shadow expulsion, coefficients of shadow matting will be produced and after that relight every pixel utilizing the light model. The yield of this evaluation framework will be the image without shadow.

V. CONCLUSION

We proposed a new approach to detect and remove shadows from a single still image. For shadow detection, we have shown that pair-wise relationship between regions provides valuable additional information about the illumination condition of regions, compared with simple appearance-based models. We also show that by applying soft matting to the detection results, our conclusions are supported by quantitative experiments on shadow detection and removal.

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