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Techniques and Algorithms of Shadow Detection in Images

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***Abstract*— Shadow detection is useful in many applications like image segmentation, scene interpretation and object recognition/tracking. Shadow in images is formed when direct light from a light source cannot reach due to obstruction by an object. Shadow removal is a critical step for improving object detection and tracking. Many algorithms for shadow detection have been proposed in the literature. This paper presents to give a survey and analysis of current shadow detection and removal methods.**

***Keywords*— Umbra;Penumbra; Cast Shadow; Self Shadow**

I. Introduction

Shadows and shadings in images occur when objects occlude light from a light source and they appear as surface features. Shadow detection is an important aspect of most object detection and tracking algorithms. Shadow points are easily misclassified as foreground since they typically differ significantly from the background. Shadow detection and removal over the past decades covers many specific applications such as traffic surveillance [1], face recognition[2] and image segmentation [3]. Image shadow detection has been a field of research for several decades. Most researches focus on providing a technique for arbitrary scene images and obtaining "visually pleasing" shadows free images. Many techniques [4] have been proposed for removing shadows from images. This paper aims to give a relatively comprehensive study on the current methods of detecting and removing shadows. In general, shadows can be divided into two major classes: Self shadow and Cast shadow.

A self shadow occurs in the portion of an object which is not illuminated by direct light. A cast shadow is the area projected by the object in the direction of direct light. Fig 1 shows some examples of different kinds of shadows in images. Cast shadows can be further classified into umbra and penumbra region, which is a result of multi-lighting and self shadows also have many sub-regions such as shading and inter-reflection. Usually, the self shadows are vague shadows and do not have clear boundaries. On the other hand, cast shadows are hard shadows and always have a violent contrast to background. Because of these different properties, algorithms to handle these two kinds of shadows are different. For instance, algorithms to tackle shadows cast by buildings and vehicles in traffic systems

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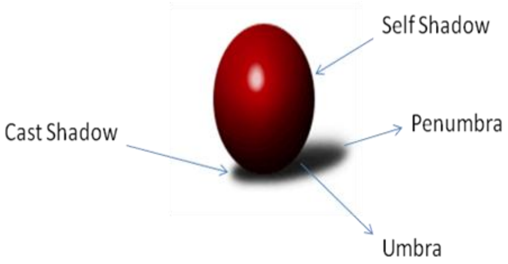
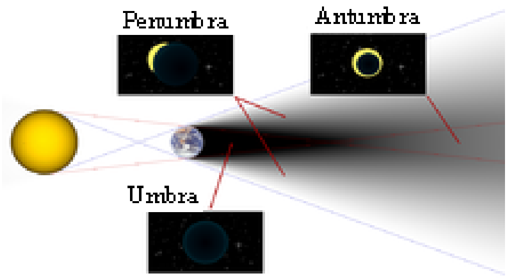
could not deal with the attached shadows on a human face.



(a)



(b)

Fig1 (a) Cast Shadow, Self Shadow, Penumbra and Umbra (b) Umbra, Penumbra and Antumbra

Accordingly, this survey attempts to classify various shadow removal algorithms by the different kind of shadows they focus on and in fact, by the different assumptions they made to the shadows. The penumbra (from the Latin paeans "almost, nearly" and umbra "shadow") is the region in which only a portion of the light source is obscured by the occluding body. An observer in the penumbra appears like a partial eclipse. The umbra (Latin for "shadow") is the darkest part of the shadow [5]. In the umbra, the light source is completely occluded. So in the umbra it is said shadows experience total eclipse. Hence it is a complete or perfect shadow of an opaque body, where the direct light from source of illumination is completely cut off. The antumbra is the region from which the occluding body appears entirely contained within the disc of the light source. If an observer in the antumbra moves closer to the light source, the apparent size of the occluding body increases until it causes a full umbra. So it appears like an annual eclipse.

II. Features of Shadow Detection

The features which are more useful for detecting shadows are

(a) Intensity

The simplest technique that can be used to detect shadows is that portion/parts under shadow become darker as they are blocked from the light source. Since there is also ambient light, there is a limit on how much darker they can become. These assumptions can be used to predict the range of intensity reduction of a region under shadow, which is often used as a first stage to reject non-shadow regions [6, 7]. However, there are no methods which rely primarily on intensity information for discriminating between shadows and objects.

(b) Chromacity

Most shadow detection methods based on spectral features use colour information. They use the assumption that regions under shadow become darker but retain their chromacity. Chromacity is a measure of colour that is independent of intensity. For instance after a green pixel is covered by shadow it becomes dark-green, which is darker than green but has the same chromacity. This color transition model where the intensity is reduced but the chromacity remains the same is normally referred to as colour constancy [8] or linear attenuation. Methods that use this model for detecting shadows often choose a colour space with better separation between chromacity and intensity

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than the RGB colour space (e.g. HSV, c1c2c3, YUV, normalized RGB, or a combination of them [9, 10, 11]. Most of these methods are simple to implement and computationally in expensive. However, because they make comparisons at the pixel-level, they are susceptible to noise. Furthermore, they are sensitive to strong illumination changes and fail with strong shadows.

(c) Physical properties

The linear attenuation model assumes that the illumination source produces pure white light, which is often not the case. In outdoors environments, the two major illumination sources are the sun(white light) and the light reflected from the sky(blue light). Normally, the white light from the sun dominates any other light source. When the sun's light is blocked, the effect of sky illumination increases, shifting the chromacity of the region under shadow towards the blue component. Nadimi and Bhanu [12] proposed a dichromatic model which takes into account both illumination sources to better predict the colour change of shadowed regions. Further work has been done to create more general non-linear attenuation models accounting for various illumination conditions in both indoor and outdoor scenarios [13]. Alternatively, some methods address the non-linear attenuation problem by learning the appearance that every pixel has under shadow without explicitly proposing an attenuation model [14, 15, 16, 17]. These methods that try to model or learn the specific appearance of shadow pixels are typically referred to as physical approaches. By learning or modeling particular scenarios, these methods tend to be more accurate than chromacity methods. However, since they are still limited to spectral properties, their main disadvantage involves dealing with objects having similar chromacity to that of the background.

(d) Geometry

In theory, the orientation, size and even shape of the shadows can be predicted with proper knowledge of the illumination source, object shape and the ground plane. Some methods use this information to split shadows from objects [18, 19, 20]. The main advantage of geometry features is that they work directly in the input frame; therefore, they do not rely on an accurate estimation of the background reference. However, methods that use geometry features impose scene limitations such as: specific object types, typically pedestrians (ie. standing people) or vehicles; requiring objects and shadows to have different orientation; and assuming a unique light source or a flat background surface. Additionally, current geometry-based methods are not designed to deal with objects having multiple shadows or multiple objects detected as a single foreground blob.

(e) Textures

Some methods exploit the fact that regions under shadow retain most of their texture. Texture-based shadow detection methods typically follow two steps :(1) selection of candidate shadow pixels or regions, and(2)classification of the candidate pixels or regions as either foreground or shadow based on texture correlation. Selection of the shadow candidates is done with a weak shadow detector, usually based on spectral features. Then, each shadow candidate is classified as either object or shadow by correlating the texture in the frame with the texture in the background reference. If a candidate's texture is similar in both the frame and the background, it is classified as shadow. Various methods perform this correlation with various techniques (e.g. normalised cross-correlation [21], gradient or edge correlation [22, 23], orthogonal transforms, Markovor conditional random fields,

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Gabor filtering. Texture correlation is a potentially powerful method for detecting shadows as textures are highly distinctive, do not depend on colours, and are robust to illumination changes. However, texture-based shadow detection methods tend to be slow as they often have to compute one or several neighborhood comparisons for each pixel.

(f) Temporal features

Finally, since moving cast shadows share the same movement pattern as the objects that produce them, the same temporal consistency filters that have been applied to the objects can be applied to the shadows. This filtering usually enhances the detection results by keeping only the pixels that are consistent in time. However, as with the intensity features, there are no methods which rely primarily on temporal features for shadow detection.

III. RELATED WORK

Andrea Cavallaro , Elena Salvador , Touradj Ebrahimi in 2002 presented an algorithm for the de-diction of local illumination changes due to shadows in real world sequences. The algorithm was designed to be able to work when camera, illumination and scene's characteristics were unknown. First colour information was exploited, and then multiple constraints from physical knowledge were embedded to define the shadow detection algorithm. Colour in- formation is exploited by means of the RGB colour space and by means of photometric invariant features. After colour analysis, a spatio-temporal veri-fication stage was introduced to refine the results. Experimental results show that the proposed algorithm outperforms state-of-the-art methods and can be applied on both indoor and outdoor image sequences.

Yasuyuki Matsushita, Member, K. Nishino 2004 proposed an illumination normalization scheme which can potentially run in real time, utilizing the illumination eigen space, which captures the illumination variation due to weather, time of day, etc., and a shadow interpolation method based on shadow hulls. This paper described the theory of the framework with simulation results and shows its effectiveness with object tracking results on real scene data sets.

Wang in 2004 suggested a three step process to remove shadows from a foreground object obtained after subtraction of an image from a background image. The first step was illumination assessment, in which the foreground region is analyzed to determine if it contains any shadow based on pixel intensity and energy. If a shadow was suspected to exist on aggregate statistics of bright and dark pixels, the shadow detection step was performed. In the final step, the object is recovered by using information from the object area and shadow attributes to construct the object.

Beril Sırmacek and Cem Unsalan in 2007 recommended a novel approach for building detection using multiple cues. We benefit from segmentation of aerial images using invariant color features. Besides, we use the edge and shadow information for building detection. We also determine the shape of the building by a novel method.

Yue Wang , Shugen Wang in 2008 preferred an edge detector . The general principle of the partial differential equations used in image restoration, a new shadow detection algorithm based on the PDES was presented, which uses the gradient values to be the parameter of edge detector. After the experiments with several urban color aerial images, it shows that the presented algorithm is effective for

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shadow detection, and no additional information is required except for the image itself.
Ruiqi Guo, Qieyun Dai Derek Hoiem in 2011 predicted relative illumination conditions between segmented regions from their appearances and perform pair wise classification based on such information. Classification results were used to build a graph of segments, and graph-cut is used to solve the labeling of shadow and non-shadow regions. Detection results were later refined by image matting, and the shadow free image was recovered by relighting each pixel based on our lighting model. We evaluate our method on the shadow detection dataset , In addition, we created a new dataset with shadow-free ground truth images, which provides a quantitative basis for evaluating shadow removal.
Andres Sanin, Conrad Sanderson, Brian Lovell in 2011 proposed physical method improves upon the accuracy of the chromacity method by adapting to local shadow models, but failed when the spectral properties of the objects were similar to that of the background. The small-region texture based method was especially robust for pixels whose neighbourhood is textured, but may take longer to implement and is the most computationally expensive. The large-region texture based method produces the most accurate results, but has a significant computational load due to its multiple processing steps.
Nijad Al-Najdawi a, Helmut E. Bez Jyoti Singhai c, Eran.A. Edirisinghe in 2012 presented a comprehensive survey of shadow detection methods, organized in a novel taxonomy based on object/environment dependency and implementation domain. In addition a comparative evaluation of representative algorithms, based on quantitative and qualitative metrics was presented to evaluate the algorithms on a benchmark suite of indoor and outdoor video sequences.
Q. YE, H. XIE, Q. XU in 2012 proposed a method to remove tall building shadows in true colour and colour infrared urban aerial images based on the theory of colour constancy. The specthem ratio and Otsu threshold segmentation methods were used to detect building shadows on urban aerial true color and color infrared aerial images. Then, based on the shadow detection result, one of the color constancy algorithms SoG (Shades of Gray) was used to remove the shadows in aerial images with different p values of the Minkowski norm. Finally, the shadow removal results with different p values have been compared by brightness, contrast and average gradients. The experiments shown that the result of this method based on color constancy has a good visual effect, and different from general scene image shadow removal, the aerial images get the best shadow removal result when p is 2. It means the two types of aerial images should not be simply regarded as gray world images.
G.L loyds Raja,Maheshkumar H.Kolekar in 2012 presented a novel method of illumination normalization based image restoration. A modified retinex algorithm was proposed to remove the shadow and restore the image. First, image was splited into illumination (L) and reflectance (R) components. The Reflectance component was subjected to threshold filtering while the illumination component was subjected to modified retinex algorithm and the resulting reflectance component was combined effectively with the output of threshold filter for obtaining the shadow-free image. Illumination normalization was performed on both small-scale as well as large-scale features. Using this approach, face images with cast shadows were normalized efficiently. The quality of the illumination normalized image was evaluated by means of JPEG quality score and PSNR values. We observed very good quality score for illumination

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normalized images in comparison with original images. The proposed method has a great potential in real-time face recognition systems, especially under harsh illumination conditions.

IV. VARIOUS ALGORITHM OF SHADOW REMOVAL

The shadow detection and removal algorithms are classified as:

(a) Chromacity-based method

Among the chromacity methods, the most important factor is to choose a colour space with a separation of intensity and chromacity. Several colour spaces such as HSV, c1c2c3 and normalised RGB have proved to be robust for shadow detection.

(b) Physical method

The basic idea behind this is when the sun's light is blocked; the effect of sky illumination increases, shifting the chromacity of the region under shadow towards the blue component. Therefore this method create more general non-linear attenuation models accounting for various illumination conditions in both indoor and outdoor scenarios Research in physical models for cast shadow removal has been done incrementally. The more recent papers are extensions of previous physical models, typically removing some assumptions and improving on previous results

(c) Geometry-based method

In this method, the orientation, size and even shape of the shadows can be predicted with proper knowledge of the illumination source, object shape and the ground plane. Most geoometry methods assume that each foreground blob contains a single object and shadow, which is not, guaranteed in many computer vision applications

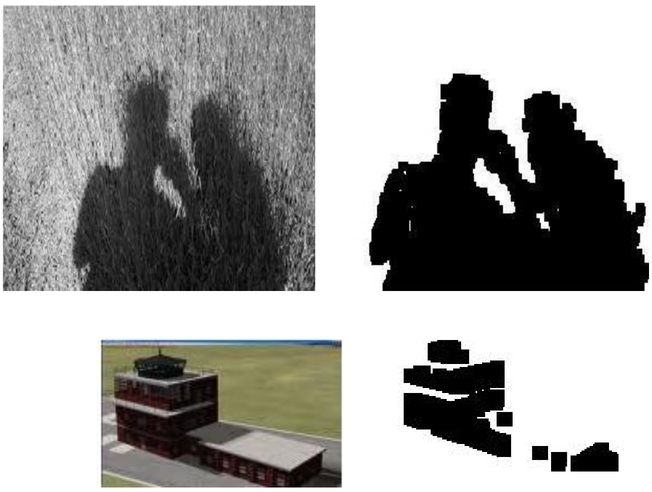
(d) Small region (SR) texture-based method

These methods exploit the fact that regions under shadow retain most of their texture. Texture-based shadow detection methods typically follow two steps: (1) selection of candidate shadow pixels or regions, and (2) classification of the candidate pixels or regions as either foreground or shadow based on texture correlation. Texture-based methods present the greatest diversity among the various categories.

(e) Large region (LR) texture-based method

The problem of using small regions is that they are not guaranteed to contain significant textures. So a method proposed using colour features to first create large candidate shadow regions (ideally containing whole shadow areas), which are then discriminated from objects using gradient-based texture correlation.

V. RESULT SHADOW DETECTION



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VI. CONCLUSION

Removing and suppressing shadows in images remains a difficult problem for computer vision systems and it is hard to measure the performance in this task.

In this paper, we have provided a comprehensive survey of shadow detection and removal in the natural scene images. The authors aimed to give a critical review of the current algorithms. Numerous representative techniques are studied and carefully categorized.

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