Pattern Recognition Letters 43 (2014) 89–97

Contents lists available at ScienceDirect

Pattern Recognition Letters

journal homepage: www.elsevier.com/locate/patrec

Shadow modelling based upon Rayleigh scattering and Mie theory

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ARTICLE INFO

Article history:
Available online 6 November 2013

Communicated by Katsushi Ikeuchi

Keywords:
Shadow detection
Shadow removal
Light scattering

ABSTRACT

In this paper, we present a method to model shadows in outdoor scenes. Here, we note that the shadow areas correspond to the diffuse skylight which arises from the scattering of the sunlight by particles in the atmosphere. This yields a treatment in which shadows in the image can be viewed as a linear combination of scattered light obeying Rayleigh scattering and Mie theory. This allows for the computation of a ratio which permits casting the problem of recovering the shadowed areas in the image into a clustering setting making use of active contours. This also opens-up the formulation of a metric that can be used to assess the degree upon which the scene is overcast. We illustrate the utility of the method for purposes of detecting shadows in real-world imagery, provide time complexity results and compare against a number of alternatives elsewhere in the literature.

1. Introduction

Shadow detection and removal is an important preprocessing step for purposes of object recognition, video surveillance and segmentation (Tian et al., 2009). This is particularly relevant in outdoor environments, where strong shadows ensue due to overcast conditions in addition to cast and self-shadowing. Despite recent interest, shadow detection in outdoor scenes remains a challenging task. Existing methods are often restricted to indoor environments (Wang et al., 2006), require prior knowledge regarding the illumination setting and geometry (Knill et al., 1997), employ multiple images (Finlayson et al., 2009) or require user input (Wu and Tang, 2005).

Indeed, a wide variety of techniques have been proposed, which employ a wide range of features and models to detect and remove cast shadows. These include chromaticity (Cucchiara et al., 2003; Salvador et al., 2004), scene or object geometry (Fang et al., 2008; Hsieh et al., 2003) and texture (Sanin et al., 2010; Leone and Distante, 2007). Along these lines, Cucchiara et al. (2003) use the HSV colour space base upon the intuition that such colour space provides a natural separation between the chromaticity and the luminosity. Salvador et al. (2004), in the other hand, use the c1c2c3 colour space, i.e. the hexadecimal RGB colour triplet, over an image region so as to reduce the effects of noise corruption.

In Salvador et al. (2004), the authors also employ the geometrical properties of the shadows. They do this by following Funka-Lea and Bajcsy (1995), who present a number of low computational cost cues for shadow recognition. Fang et al. (2008) employ a geometry model, whereby they assume the scene background to be a flat surface. In an alternative approach, Hsieh et al. (2003) separate the scenes into blobs so as to recover individual objects for purposes of geometric analysis. Their method hinges in the notion that, as the blobs corresponding to objects in the scene may have different orientations, the extreme points in the blobs can be used to recover shadow-object pairs based upon a Gaussian model defined in terms of the pixel coordinates and their intensities.

As mentioned earlier, textures have also been used for shadow detection. This hinges in the rationale that texture correlation is expected to be invariant to illumination changes and, hence, robust to shadowing. This is exploited by Leone and Distante (2007), who describe textural information in terms of redundant systems of functions so as to improve the background model used for shadow detection. Sanin et al. (2010) use gradient-based texture correlation to discriminate amongst candidate shadow regions.

Alternative approaches include shadow flows (Porikli and Thornton, 2005), i.e. a disparity vector computed by comparing a shadow model with a background model, multiple views and the use of user input. This is the case for the work presented in Finlayson et al. (2009), where the authors recover a shadow-free image based upon the assumption that the illumination varies slowly and, hence, gives rise to the small gradients in each view. As a result, large gradients depend on reflectance changes. The shadow-free image is then compared with the input image so as to recover the shadow edges via thresholding.

[1] NICTA is funded by the Australian Government as represented by the Department of Broadband, Communications and the Digital Economy and the Australian Research Council through the ICT Centre of Excellence program.

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http://dx.doi.org/10.1016/j.patrec.2013.10.020

As related to the use of user input, in Wu and Tang (2005), a probabilistic method and matting are used to remove shadows based upon a quadmap (Wu et al., 2007). The application of statistics is somewhat related to the method in Wang et al. (2006), where a dynamic conditional Markov random field is used to detect shadows and perform background subtraction in indoor scenes. In Martel-Brisson and Zaccarin (2005), the authors employ a Gaussian mixture model to characterise the moving cast shadows on the surfaces across the scene.

In this paper, we tackle the problem of detecting shadows in outdoor environments by viewing the shadowed areas in the image as being lit by skylight, whereas the non-shadowed regions in the image are illuminated by both, skylight and sunlight. This is akin to the treatment presented in Gu and Robles-Kelly (2012), where the authors detect shadows using Rayleigh and Mie scattering theory. Following Gu and Robles-Kelly (2012), we note that the edges in the image produced by shadows should correspond to a mix of sunlight to skylight whose ratio is constant throughout the scene.

This paper is, hence, a natural extension of Gu and Robles-Kelly (2012) with a number of major improvements. Firstly, spherical harmonics are used so as to achieve the relaxation of the single point light source assumption in Gu and Robles-Kelly (2012). This is an important theoretical development since it assures our method holds for complex sky luminance patterns, where the direction of the skylight that illuminates the area of interest can depart greatly from a single point light source assumption. This is as light scattered by cloud and haze can follow multiple paths, impinging the object surface from arbitrary directions. We use these spherical harmonics so as to cast the problem into a segmentation setting where techniques such as active contours (Blake et al., 1998) can be used to detect the shadows in the image. This yields a result in accordance with that in Gu and Robles-Kelly (2012), where the active contour evolution is governed by a ratio that arises from the use of Rayleigh scattering and Mie theory to model the skylight illuminating the shadowed areas.

Secondly, here we note that, in practice, the shadow area is not always distinct from sunlit area. This is particularly true for the fringe of the shadows in the image, where the transition region, i.e. penumbra, consists of sunlight and skylight mixed with one another. Thus, here, instead of segmenting the image in a binary setting, we recover the proportion of sunlight to skylight along the penumbra area. We illustrate how recovering the exact proportion of these two components can be tackled using image matting by post-processing the shadow boundary with KNN Matting (Chen et al., 2013).

Thirdly, we propose a weather metric so as to estimate meteorological conditions from single images. Our metric contrasts in simplicity with other methods elsewhere in the literature which aim at inferring atmospheric phenomena for the sky appearance. For instance, the International Commission on Illumination (CIE) has established a standard sky model (CIE, 2002) with five degrees of freedom. This model, proposed by Preetham et al. (1999), depends upon five parameters which account for different weather conditions and climates. Despite effective, the model's complexity makes it cumbersome to use in practical settings. As a result, researchers have attempted to use a single parameter, i.e. turbidity, to describe the effect of Mie scattering effect. We remit the interested reader to the detailed description in the classic book by Minnaert (1954).

It is also worth noting that here we use a wavelength dependent Mie scattering term. This contrasts with the one used in Gu and Robles-Kelly (2012), where a simplified expression devoid of wavelength dependence was used. Thus, the method described here relies on the estimation of model parameters before shadow detection. We tackle this drawback by applying an initialisation step which estimates the initial model parameters from the input image. The initialisation presented here is robust to various weather conditions.

The paper is organised as follows. In the following section, we model the skylight as a linear combination of the Rayleigh and Mie scattered light. With this linear combination at hand, we then present the ratio used for the evolution of the active contour, which we present in Section 4. From the ratio, we propose a weather metric to estimate the meteorological condition of clouds obscuring the sky. This is, we propose a method to appraise the degree upon which the sky is overcast based upon a single parameter. We elaborate on the implementation of our method in Section 5. Finally, we present results and conclusions in Sections 6 and 7, respectively.

2. Rayleigh scattering and Mie theory

As mentioned earlier, here, we note that, in outdoor scenes, the shadowed areas correspond to the diffuse skylight which arises from the scattering of the sunlight by particles in the atmosphere (Narasimhan and Nayar, 2002). Thus, we employ the Rayleigh scattering and Mie theory of sunlight propagation in the atmosphere to model the shadows.

Recall that, when sunlight enters the atmosphere, it is scattered by the particles in the air. When these particles are small as compared to the wavelength of the impinging light (typically less than 1 tenth the wavelength), the scattering can be approximated by the proportion of the fourth power of the wavelength of the sun light, i.e. the Rayleigh scattering (Kerker, 1969). It is worth noting in passing that this provides a physical explanation for the sky being blue, as the blue light in shorter in wavelength and, hence, is scattered much more than the red light corresponding to longer wavelengths. The Rayleigh scattering is given by

$$E_{Rayleigh} = \frac{8\pi^3(r^2-1)^2}{3N\lambda^4}\left(\frac{6+3p_n}{6-7p_n}\right)E(\lambda) \tag{1}$$

where $E(\lambda)$ is the power spectrum of the illuminant at wavelength λ, $r = 1.0003$ is the refractive index of air in the visible spectrum, $N = 2.545 \times 10^{25}$ is number of molecules per unit volume and p_n is the depolarization factor, which is considered to be 0.035 for air.

However, when the sunlight is scattered by particles bigger or of equal size to the wavelength, the scattering phenomenon is modelled by Mie theory (Kerker, 1969). Mie theory states that the scattering is proportional to the second power of the wavelength. Mie theory is generally employed to model the scattering caused by haze in the atmosphere. This is as light scatters more uniformly across wavelengths, which causes a whitewash appearance in haze and cloud. Mie scattering is given by

$$E_{Mie} = 0.434Bc\pi\left(\frac{2\pi}{\lambda}\right)^{v-2}E(\lambda) \tag{2}$$

where c is the concentration factor that varies with turbidity T in the inteval $(0.6544T - 0.6510) \times 10^{(-16)}$, v is Junge's exponent with a value of 4 for the sky and $B = 0.68$ in the visible spectrum.

Thus, both, Mie theory and Rayleigh scattering must be taken into account for modelling the skylight. This is as the air in the atmosphere will account for a large fraction of the Rayleigh scattering whereas Mie theory is bound to apply to clouds and dust. Both the Rayleigh and Mie scattered light compose the skylight and, hence, we can write

$$E_{sky}(\lambda) = (1-p_c)E_{Rayleigh}(\lambda) + p_cE_{mie}(\lambda) \tag{3}$$

where, λ is the wavelength parameter, p_c is the contribution of the Mie scattering and $E_{mie}(\lambda)$ and $E_{rayleigh}(\lambda)$ corresponds to the Rayleigh scattered light. This equation would be further simplified as