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Shadow detection in very high spatial resolution aerial images: A comparative study

K.R.M. Adeline [a,b,*,1], M. Chen [c,d,*,1], X. Briottet [a], S.K. Pang [c,e], N. Paparoditis [f]

[a] ONERA, The French Aerospace Lab, 2 avenue Edouard Belin, BP 74025, 31055 Toulouse Cedex 4, France
[b] Université de Toulouse, Institut Supérieur de l'Aéronautique et de l'Espace (ISAE), Toulouse 31055, France
[c] DSO National Laboratories, 20 Science Park Drive, Singapore 118230, Singapore
[d] Nanyang Technological University, School of Computer Engineering, 50 Nanyang avenue, Singapore 639798, Singapore
[e] National University of Singapore, 21 Lower Kent Ridge Road, Singapore 119077, Singapore
[f] Université Paris-Est, IGN, IGN labs, MATIS, 73 avenue de Paris, 94160 Saint-Mandé, France

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ABSTRACT

Automatic shadow detection is a very important pre-processing step for many remote sensing applications, particularly for images acquired with high spatial resolution. In complex urban environments, shadows may occupy a significant portion of the image. Ignoring these regions would lead to errors in various applications, such as atmospheric correction and classification. To better understand the radiative impact of shadows, a physical study was conducted through the simulation of a synthetic urban canyon scene. Its results helped to explain the most common assumptions made on shadows from a physical point of view in the literature. With this understanding, state-of-the-art methods on shadow detection were surveyed and categorized into six classes: histogram thresholding, invariant color models, object segmentation, geometrical methods, physics-based methods, unsupervised and supervised machine learning methods. Among them, some methods were selected and tested on a large dataset of multispectral and hyperspectral airborne images with high spatial resolution. The dataset chosen contains a large variety of typical occidental urban scenes. The results were compared based on accurate reference shadow masks. In these experiments, histogram thresholding on RGB and NIR channels performed the best with an average accuracy of 92.5%, followed by physics-based methods, such as Richter's method with 90.0%. Finally, this paper analyzes and discusses the limits of these algorithms, concluding with some recommendations for shadow detection.

1. Introduction

Shadow analysis has been widely used in many remote sensing applications. For instance, with low resolution satellite sensors, cloud shadows are corrected with the assumption of a flat scene (Wang et al., 1999). However, with the advent of new sensors with higher spatial resolution, careful consideration of shadows caused by the geometry of the scene has become increasingly important for landscapes such as mountainous (Giles, 2001) and urban environments (Dare, 2005).

Ignoring the radiative impact of shadows would result in an erroneous estimation of material properties in shadows such as reflectance (Lachérade et al., 2008; Leblon et al., 1996). In the one hand, radiometric distortions in shadows would degrade the performance of many applications like object recognition, land-cover mapping (Chen et al., 2009; Lachérade et al., 2008), target detection (Shimoni et al., 2011), video tracking (Chen et al., 2011), 3D reconstruction, traffic monitoring (Fleyeh, 2006), etc. As such, shadow detection would be the first necessary preprocessing step to improve the outcome of these techniques. On the other hand, shadows could be considered as a source of semantic and geometrical information. Some urban applications such as building 3D reconstruction from shadows utilize shadow spatial features like shape or length (Irvin and McKeown, 1989; Liow and Pavlidis, 1990), and the direction of sunlight (Guo et al., 2008; Shettigara and Sumerling, 1998). In this case, automated shadow detection would facilitate the automatic extraction of such parameters from the scene.

There are existing literature surveys on shadow detection methods. However, most of them only deal with photographic images (Xu et al., 2006) or video sequences (Prati et al., 2001). Up to now, none of them surveys shadow detection methods of a single aerial image with a very high spatial resolution for both multispectral and hyperspectral data in urban environments. As such, the issue of the paper is to comparatively study the current state-of-the-art algorithms on shadow detection and to evaluate the performance of selected methods on both multispectral and

* Corresponding authors.
E-mail addresses: karine.adeline@gmail.com (K.R.M. Adeline), marcuschen08@gmail.com (M. Chen).
[1] These authors contributed equally to this work.

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hyperspectral data. For the purposes of automation, priority was given to methods that require few user-input parameters. A test dataset of many urban and suburban areas was collated, with spatial resolution ranging from 0.12 m to 0.50 m. The accuracy of the selected methods was then assessed by comparison to accurate reference shadow masks that were manually created.

The paper is organized as follows. In Section 2, this paper briefly describes the radiative impact of shadows, illustrated by the simulation results of a synthetic scene. Section 3 reviews some methods of shadow detection and selects the most appropriate algorithms for further analysis. Section 4 introduces the dataset and performance measures. The experimental results are presented and discussed in Section 5. Finally the paper concludes in Section 6 with some recommendations.

2. Physical considerations on shadow

This section introduces the notions of the radiative budget of shadowed regions in comparison with sunlit areas. Some fundamentals will be described in Section 2.1 and followed by a detailed analysis explaining the relative contribution of each radiative component at ground and sensor level in Section 2.2. Such analysis will help in understanding the main assumptions used in state-of-the-art shadow detection algorithms in Section 3.

2.1. Preliminaries

Shadows are formed when a fraction of direct light from a source of illumination is blocked. Shadows can be categorized into two classes: self-shadows and cast shadows (Arévalo et al., 2008). Self-shadow occurs on the portion of the object which is not illuminated by the direct light; whereas cast shadow is projected by the object in the direction of sunlight. Cast shadows can be further categorized into the umbra and penumbra. In the umbra, the direct light is fully obscured, whereas for the penumbra, only a fraction of direct light is blocked. The penumbra is often located at the transition between umbra and sunlit regions in the scene and as a result it may be ambiguous on the image. Fortunately, it generally only occupies a small percentage of cast shadow. Based on Dare (2005), for a building height of 15 m in Toulouse, France, a solar disk size of 0.533°, a sun zenith angle of 32.2°, the size of the penumbra is about 0.2 m. This implies that for very high spatial resolution data, the penumbra size could be of the same order of magnitude as pixel size. This paper does not distinguish penumbra from umbra, but its impact on the performance results will be further discussed in Section 5.

2.2. Radiative transfer considerations

Besides appearing darker, shadows have other less obvious properties that have been used in literature for shadow detection. These properties can be better explained in a radiometric framework, especially in terms of the different contribution of the radiative components at both ground and sensor level in shadowed and sunlit areas. A simulation with a synthetic urban scene is included for illustration purposes.

First, the radiative components are introduced as in Fig. 1. At the ground level, the total irradiance I_{total} is composed of four main components (Eq. (1)): direct solar irradiance I_{direct}, downwelling atmospheric irradiance due to the light scattered by the atmosphere $I_{diffused}$, irradiance due to the reflection of the light from surrounding targets $I_{reflected}$ and irradiance due to the multiple scattering between the ground and the atmosphere $I_{coupling}$.

At the sensor level, the radiance incident to the sensor R_{sensor} is composed of three components (Eq. (2)): direct radiance R_{direct} directly transmitted from the target to the sensor, scattered radiance $R_{environment}$ due to the light reflected by the surrounding target and scattered by the atmosphere in the sensor field of view and upwelling atmospheric radiance $R_{atmospheric}$.

$$I_{total} = I_{direct} + I_{diffused} + I_{reflected} + I_{coupling} \tag{1}$$

$$R_{sensor} = R_{direct} + R_{environment} + R_{atmospheric} \tag{2}$$

To illustrate the relative amount of these different radiative components, simulations have been carried out using a synthetic scene as shown in Fig. 2a, which corresponds to a typical urban canyon. Lambertian surface reflectances were input for the scene: tiles for the roofs, bricks for the building walls, and two different materials for the ground, namely asphalt (low reflectance) and grass (non-flat spectrum). These two materials were chosen for the ground in order to assess the impact of material reflectance within shadow. These reflectance spectra are plotted in Fig. 2b. The radiative simulations are computed with Amartis V2 (Thomas et al., 2011). The radiative transfer code, 6SV (Vermote et al., 1997), is used to obtain the atmospheric parameters, such as the atmospheric transmittance and radiances. The inputs are the atmosphere type (mid-latitude summer) and aerosols (urban type, visibility of 23 km), along with the solar and viewing geometry (20° solar zenith angle and a nadir viewing angle). The simulation results are shown in Fig. 3.

Firstly, considering asphalt as the ground material, it can be seen that the direct irradiance contributes the most to the total irradiance in sunlit regions, amounting up to 85% of the total irradiance (Fig. 3a). In shadowed regions, the absence of direct irradiance results in a much lower amount of total irradiance. Instead, shadows mainly receive scattered light (diffused and coupling) and reflected light, as observed in Fig. 3b. Scattering effects significantly decrease towards longer wavelengths, from approximately 85% to 5%. The contribution of reflected light is dependent on the surrounding materials, as well as their spectral behavior. Its contribution can reach more than 50% of the total irradiance in shadows for the urban canyon scenario that was chosen.

At sensor level (Fig. 3c), the direct radiance is the major component in sunlit regions. Its values vary between 50% and 95% across the bands, and they depend on the underlying material reflectance. In shadowed regions, a smaller total irradiance causes a smaller direct radiance. In this case, the main contribution is from scattered light (atmospheric and environment), which accounts for more than 70% of the sensor radiance. Overall, shadow regions remain darker than their sunlit counterparts.

Secondly, comparing the sensor radiances of asphalt and grass as ground materials, it can be observed from Fig. 3d that for the same external conditions, the radiance behavior is influenced by the spectral properties of material within shadow; this may explain the misclassification of some high reflectance materials in shadow as sunlit because they appear much brighter than their lower reflectance counterparts in shadows.

The observations from this non-exhaustive simulation can be generalized to the following conclusions about shadow behavior:

- *Property no. 1*: Shadows tend to have much lower sensor radiance than their sunlit counterparts over the whole reflective spectrum.
- *Property no. 2*: In constrained environments like an urban scene, reflection effects due to the 3D surroundings may not be negligible.
- *Property no. 3*: Sensor radiance received from shadowed regions decreases from short to long wavelengths due to scattering, so that it is easier to distinguish shadows from non-shadows with NIR channels rather than visible channels.