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Radiometric normalization and cloud detection of optical satellite images using invariant pixels

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ABSTRACT

Clouds in optical satellite images can be a source of information for water measurement or viewed as contaminations that obstruct landscape observations. Thus, the use of a cloud detection method that discriminates cloud and clear-sky pixels in images is necessary in remote sensing applications. With the aid of radiometric correction/normalization, previous methods utilized temporal and spectral information as well as cloud-free reference images to develop threshold-based cloud detection filters. Although this strategy can effectively identify cloud pixels, the detection accuracy mainly relies on the successful radiometric correction/normalization and reference image quality. Relative radiometric normalization generally suffers from cloud covers, while multi-temporal cloud detection is sensitive to the radiometric normalization quality. Thus, the current study proposes a method based on weighted invariant pixels for both processes. A set of invariant pixels is extracted from a time series of cloud-contaminated images by using the proposed weighted principle component analysis, after which multi-temporal images are normalized with the selected invariant pixels. In addition, a reference image is generated for each cloud-contaminated image using invariant pixels with a weighting scheme. In the experiments, image sequences acquired by the Landsat-7 Enhanced Thematic Mapper Plus sensor are analyzed qualitatively and quantitatively to evaluate the proposed method. Experimental results indicate that *F*-measures of cloud detections are improved by 1.1–6.9% using the generated reference images.

1. Introduction

Passive remote sensing sensors used for Earth observations are primarily limited by their sensitivity to clouds and weather conditions. An average of approximately 35% of land scenes are covered by clouds (Ju and Roy, 2008). Thus, the availability of accurate cloud masks is vital in related research topics, such as atmospheric correction, vegetation/forest monitoring, land cover classification, and land use change detection. Clouds appear identifiable as they are generally bright in images. However, the variety of reflectance and temperatures of the Earth's surface make it difficult to accurately identify clouds from images. Therefore, the automatic and accurate generation of cloud masks remains a challenging and important issue for the remote sensing community. The detection of clouds in satellite imagery using the temporal information is sensitive to the radiometric normalization quality; moreover, such normalization generally suffers from cloud cover. Therefore, this study proposes a new method for both radiometric normalization and cloud mask generation.

Many cloud detection methods have been proposed. Based on the acquisition time of the data used in detection algorithms, these methods are classified into two categories, namely, single-date and multi-temporal methods. Single-date methods utilize spectral and contextual information in cloud detection with the available spectral bands and sensors. Thresholding on thermal bands is the most common approach (Ackerman et al., 1998; Bréon and Colzy, 1999; Irish et al., 2006; Hulley and Hook, 2008; Hagolle et al., 2010; Zhu and Woodcock, 2012; Jin et al., 2013). A temperature threshold is specified to separate cloud and clear-sky pixels based on the fact that clouds are bright in the thermal bands. For example, Irish et al. (2000, 2006) proposed an automatic cloud cover assessment (ACCA) for images acquired by the Landsat-7 Enhanced Thematic Mapper Plus (ETM+) sensor. Their method uses available bands to establish a set of threshold-based filters. Several reflectance ratios on bands 2–6 are used to partition the pixels into clouds, non-clouds, and ambiguous pixels. The ambiguous pixels are further re-examined solely by thresholding band 6 (i.e., the thermal band). Hulley and Hook (2008) and Oreopoulos et al. (2011)

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proposed adaptations of ACCA to process images obtained from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and Moderate Resolution Imaging Spectroradiometer (MODIS) sensors. Although ACCA can effectively detect clouds, this algorithm may fail to distinguish snow from clouds in high-latitude areas (Zhu and Woodcock, 2012). To resolve this problem, Choi and Bindschadler (2004) developed a method to determine the optimal threshold of the normalized difference snow index (NDSI) by iteratively matching clouds and cloud shadow edges. Zhu and Woodcock (2012) utilized top of atmosphere (ToA) reflectance and temperatures in cloud and cloud shadow detection.

Although thermal bands are effective for cloud detection, the payload of several Earth observation sensors with high spatial resolution does not include thermal channels. Therefore, several methods that utilize multiple sensors and contextual information have been proposed. Sedano et al. (2011) proposed a multi-sensor method, which relies on complementary information provided by a second sensor with a high revisit period. In addition, several studies adopted advanced algorithms, such as linear spectral unmixing (Tseng et al., 2008), Markov random field (Hégarat-Mascle and André, 2009) and tasseled cap transformation (Li and Tang, 2013), to detect clouds using the spatial correlation and contextual information of an image.

Compared with single-date methods, multi-temporal methods that utilize temporal and spectral information potentially have better performance in terms of detection accuracy. The method proposed by Lyapustin et al. (2008) is based on the hypothesis that clouds are present if there is low temporal correlation between two temporally successive images. Similarly, Derrien and Gleau (2010) utilized temporal differencing in cloud grouping, while Goodwin et al. (2013) regarded clouds as high reflectance outliers in a time series sequence. Different from the aforementioned methods, Hagolle et al. (2010) and Tang et al. (2013) utilized temporal information and a cloud-free reference image in cloud masking. Temporal variations in the blue band between a cloud-contaminated image and its most recent cloud-free image are used to mark the clouds initially. Potential false detections are then prevented by applying several criteria, including the comparison of the reflectance variations in the blue and red spectral bands as well as the local correlation test between two successive images.

With the aid of cloud-free reference images in filtering, a few methods (Hagolle et al., 2010; Tang et al., 2013) can potentially outperform the related methods when a high-confidence reference image is available. However, an existing cloud-free image is rare, and generating a reference image for each cloud-contaminated image remains a challenging problem. Although several methods that compose cloud-free pixels or patches from multi-temporal images to form a cloud-free image have been proposed (Wang et al., 2014; Lin et al., 2013, 2014), these require information on cloud masks. In the current study, both cloud-free reference image generation and cloud mask generation are considered and solved using weighted invariant pixels. By utilizing temporal information, a set of radiometric invariant pixels is extracted from multi-temporal images using the proposed weighted principal component analysis (PCA). The obtained invariant pixels are then used in performing radiometric normalization and generating a reference image for each cloud-contaminated image. These processes ensure the feasibility of automatic and accurate cloud masking.

2. Background

The proposed method is based on radiometric normalization (Du et al., 2002) and multi-temporal cloud detection (Hagolle et al., 2010). Therefore, these two methods are briefly introduced in this section.

2.1. Review of radiometric normalization

In the relative radiometric normalization of two images of the same region acquired at different times, a regression process is generally required to determine a linear transformation between the bitemporal images. The key to the regression is the selection of invariant pixels, or called pseudo-invariant features (PIFs). Du et al. (2002) proposed the use of PCA to select PIFs based on the following assumptions: (1) variations in the digital counts of PIFs during the period are linear and spatially homogeneous; (2) the consistently changed targets are not the majority of targets in each scene; and (3) the effects causing changes in the image digital counts for PIFs are independent of one another. The scatterplot of the bitemporal images resembles an ellipse represented by major and minor principal axes. The pixels around the major axis are considered invariant pixels. The method iteratively probes for a suitable range around the major axis until an acceptable correlation coefficient of the invariant pixels is obtained. Outliers in the scatterplot, such as cloud and water pixels, are rejected prior to the PCA computation to extract the major axis accurately.

Given two sets of invariant pixels (P_a, P_b) in two images acquired at times a and b, the linear transformation between these two sets is formulated as

$$\overline{P}_a = \overline{P}_b \times \alpha + \beta, \tag{1}$$

where α and β are the transformation coefficients. In addition, $\overline{P}_a = \frac{1}{p}\sum_{k=1}^{p} P_a(k)$ and $\overline{P}_b = \frac{1}{q}\sum_{k=1}^{q} P_b(k)$, where p and q represent the number of invariant pixels in P_a and P_b, respectively. Given a series of images and their corresponding invariant pixels, Du et al. (2002) suggested the transformation of all images on a common radiometric scale and the normalization of images to a reference level denoted by P_{ref}. To preserve the radiometric resolution, the standard deviation σ_{ref} and the mean $\overline{P}_{ref}$ of the reference level are determined by

$$\sigma_{ref} = \max\left(\sigma_{P_k}\right)_{k=1}^{n_i}; \quad \overline{P}_{ref} = \max\left(\frac{\sigma_{ref}}{\sigma_{P_k}} \times \overline{P}_{ref}\right)_{k=1}^{n_i}, \tag{2}$$

where n_i represents the number of images in an image sequence. The transformation coefficients of each image are calculated based on the determined reference level by

$$\alpha_k = \frac{\sigma_{ref}}{\sigma_{P_k}} \text{ and } \beta_k = \overline{P}_{ref} - \frac{\sigma_{ref}}{\sigma_{P_k}} \times \overline{P}_k, \quad k = 1, \cdots, n_i \tag{3}$$

The PCA-based regression can effectively obtain the radiometric transformation coefficients. However, the PCA computation is sensitive to the inherent outliers in the scatterplot owing to the non-robust statistical analysis. To obtain a reliable major axis and to improve the radiometric normalization results, a method that utilizes the weighted PCA is proposed, which is described in Section 3.3.

2.2. Review of multi-temporal cloud detection

A cloud-free reference image is required in the cloud detection method (Hagolle et al., 2010). Assume that a reference image, denoted by $I_{D_{ref}}$, acquired at day D_{ref} is available. The first criterion in cloud detection is measuring the reflectance differences of the blue bands in a cloud-contaminated image and in the reference image, that is,

$$ToA_{blue}(I_D) - ToA_{blue}(I_{D_{ref}}) > 0.03 \times \left(1 + (D - D_{ref})/30\right), \tag{4}$$

where $ToA_{blue}(I_D)$ is the pixel ToA reflectance in the blue band of the cloud-contaminated image I_D captured on day D. The threshold value relates to the number of days between D and D_{ref}. The