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Multi-feature combined cloud and cloud shadow detection in GaoFen-1 wide field of view imagery

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ABSTRACT

The wide field of view (WFV) imaging system onboard the Chinese GaoFen-1 (GF-1) optical satellite has a 16-m resolution and four-day revisit cycle for large-scale Earth observation. The advantages of the high temporal-spatial resolution and the wide field of view make the GF-1 WFV imagery very popular. However, cloud cover is an inevitable problem in GF-1 WFV imagery, which influences its precise application. Accurate cloud and cloud shadow detection in GF-1 WFV imagery is quite difficult due to the fact that there are only three visible bands and one near-infrared band. In this paper, an automatic multi-feature combined (MFC) method is proposed for cloud and cloud shadow detection in GF-1 WFV imagery. The MFC algorithm first implements threshold segmentation based on the spectral features and mask refinement based on guided filtering to generate a preliminary cloud mask. The geometric features are then used in combination with the texture features to improve the cloud detection results and produce the final cloud mask. Finally, the cloud shadow mask can be acquired by means of the cloud and shadow matching and follow-up correction process. The method was validated using 108 globally distributed scenes. The results indicate that MFC performs well under most conditions, and the average overall accuracy of MFC cloud detection is as high as 96.8%. In the contrastive analysis with the official provided cloud fractions, MFC shows a significant improvement in cloud fraction estimation, and achieves a high accuracy for the cloud and cloud shadow detection in the GF-1 WFV imagery with fewer spectral bands. The proposed method could be used as a preprocessing step in the future to monitor land-cover change, and it could also be easily extended to other optical satellite imagery which has a similar spectral setting. The global validation dataset and the software tool used in this study have been made available online (http://sendimage.whu.edu.cn/en/mfc/).

1. Introduction

Clouds and the accompanying shadows are inevitable contaminants for optical imagery in the range of the visible and infrared spectra. The global annual mean cloud cover is approximately 66% according to the estimation of the International Satellite Cloud Climatology Project-Flux Data (ISCCP-FD) (Zhang et al., 2004). Cloud cover impedes optical satellites from obtaining clear views of the Earth's surface, and thus the existence of clouds influences the availability of useful satellite data. Cloud shadows cast by clouds are also a contaminant for imagery, and the dark effect of cloud shadows results in the spectral information of the imagery covered by cloud shadows being partly or entirely lost. The cloud and cloud shadows in the imagery affect the processing of the imagery, in applications such as classification, segmentation, feature extraction, etc. A number of cloud removal and image restoration methods (Zeng et al., 2013; Cheng et al., 2014; Li et al., 2014; Shen et al., 2014) can effectively repair cloud-contaminated imagery, but they do not provide a specific way to automatically extract the clouds. Accurately extracting clouds and cloud shadows from cloud-contaminated imagery can help to reduce the negative influences that cloud coverage brings to the application of the imagery. Furthermore, cloud cover estimation can be used for imagery availability evaluation. Therefore, cloud and cloud shadow detection in optical imagery is of great significance.

The GaoFen-1 ("GaoFen" means high resolution in Chinese) satellite was launched by the China Aerospace Science and Technology Corporation (CASC) in April 2013. It was the first of a series of satellites in the civilian High-Definition Earth Observation Satellite (HDEOS) program to realize a high-resolution and wide-swath optical remote sensing mission. The wide field of view (WFV) imaging system is one of the key

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instruments operating onboard the GF-1 satellite, as shown in Fig. 1. It includes four integrated cameras with a 16-m spatial resolution and four-day temporal resolution. Each WFV camera has four multispectral bands, spanning the visible to the near-infrared spectral regions, and shares similar band passes to Landsat ETM+ (Table 1). The swath width of the GF-1 WFV imaging system increases to 800 km when the four cameras are combined, which significantly improves the capabilities for large-scale surface observation and monitoring. The images of the four cameras are delivered separately in level-1A and level-2A products. The level-1A data are raw digital products with the process of homogenized radiation calibration, while the level-2A data are produced after systematic geometric correction, in which the pixels are all resampled to a 16-m resolution. The imagery of the GF-1 satellite has served a wide range of applications covering many topics. The typical applications include disaster prevention and relief, geographical mapping, environment and resource surveying, as well as precision agriculture support (Chen et al., 2015b; Li et al., 2015a,c; Lu & Bai, 2015; Wang et al., 2015).

Cloud detection in GF-1 WFV imagery is a challenging task because of the unfixed radiometric calibration parameters and the insufficient spectral information. The GF-1 WFV imaging system also lacks onboard calibration capabilities (Yang et al., 2015), which makes accurate calibration of GF-1 imagery difficult. In addition, this kind of imagery has no thermal infrared band or water vapor/CO_2 absorption band, which is critical for cloud identification (Huang et al., 2010). Due to the lack of sufficient spectral information, it is not easy to separate clouds from some bright ground objects (such as snow, buildings, and coast lines) when only using the spectral features. Meanwhile, thin cloud is also hard to detect in optical satellite imagery because of the different underlying surfaces. Moreover, it is usually difficult to capture the complete cloud shadow location because of shadow screening and cloud shadow matching errors. In order to acquire better cloud and cloud shadow detection results based on limited spectral bands, more features such as geometric and texture features should be taken into consideration.

2. Background

In recent years, scholars have undertaken a great deal of research into cloud and cloud shadow detection for different types of remote sensing data, such as AVHRR (Di Vittorio & Emery, 2002; Khlopenkov & Trishchenko, 2007), MODIS (Platnick et al., 2003; Luo et al., 2008), and Landsat series imagery (Irish et al., 2006; Zhu & Woodcock, 2012; Goodwin et al., 2013; Harb et al., 2016). The methods of cloud detection can be divided into two categories according to the single or multi-temporal scenes the algorithm uses.

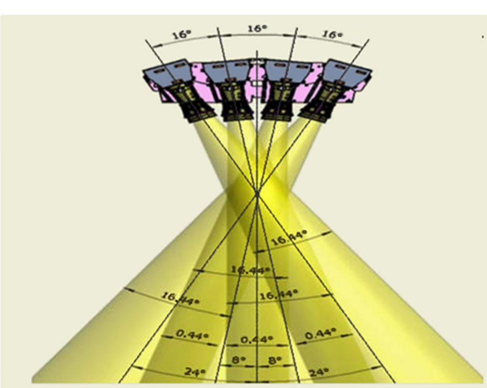
Cloud detection methods based on a single scene are more popular than multi-temporal methods, due to the reduced requirement for input data. The automatic cloud cover assessment (ACCA) algorithm (Irish et al., 2006) was designed for the cloud cover assessment of Landsat-7 imagery. The ACCA algorithm is an official method and is included in the Landsat-7 Science Data User's Handbook (Irish, 2000). In order to further capture the thin clouds which cannot be effectively detected by the ACCA algorithm in Landsat imagery, function of mask (Fmask) (Zhu & Woodcock, 2012; Zhu et al., 2015), which is a robust cloud detection method, was proposed for routine usage with Landsat images. Haze optimized transformation (HOT) (Zhang et al., 2002; Zhang et al., 2014) was also developed for the detection and characterization of haze/cloud in Landsat scenes, but it requires prior knowledge of the image to build a clear line in spectral space to separate haze/cloud from the clear surfaces. Le Hégarat-Mascle and André (2009) and Vivone et al. (2014) developed cloud detection algorithms based on Markov random fields. Fisher (2014) implemented morphological feature extraction to detect cloud and cloud shadow in high-resolution SPOT imagery. In addition, methods based on machine learning have also been applied in automatic cloud detection, including the spatial procedures for automated removal of cloud and shadow (SPARCS) algorithm (Hughes & Hayes, 2014), which uses a neural network to identify cloud and cloud shadow in Landsat scenes, and a cloud image detection method based on support vector machine (Li et al., 2015b).

Table 1
Spectral range comparison between GF-1 WFV and Landsat ETM+ imagery.

Bandwidth (μm)	GF-1 WFV	Landsat ETM+
Band 1 (Blue)	0.45–0.52	0.45–0.52
Band 2 (Green)	0.52–0.59	0.52–0.60
Band 3 (Red)	0.63–0.69	0.63–0.69
Band 4 (NIR)	0.77–0.89	0.76–0.90
Band 5 (SWIR-1)	–	1.55–1.75
Band 6 (TIR)	–	10.4–12.5
Band 7 (SWIR-2)	–	2.08–2.35
Band 8 (Pan)	–	0.50–0.90

Compared to the single-image cloud detection methods, multi-temporal cloud detection methods usually achieve a higher cloud detection accuracy. However, these methods require more scenes over a short time period to ensure that the land cover in the same place does not change much. Therefore, multi-temporal cloud detection methods may be more suitable for relatively permanent land areas in high temporal resolution imagery. Examples of multi-temporal cloud detection methods include the multi-temporal cloud detection (MTCD) method (Hagolle et al., 2010), the multi-temporal cloud and snow detection algorithm (Bian et al., 2014) for the HJ-1A/1B CCD imagery of China, the multi-temporal mask (Tmask) for the automatic masking of cloud, cloud shadow, and snow for multi-temporal Landsat images (Zhu & Woodcock, 2014), and the optical satellite imagery cloud detection method using invariant pixels (Lin et al., 2015).

Cloud shadow detection is usually undertaken after cloud detection (Luo et al., 2008; Hughes & Hayes, 2014; Fisher, 2014; Braaten et al., 2015). Shadows in remote sensing imagery can be approximately



Items	Parameters
orbit type	sun synchronous orbit
average orbit height	644.5km
descending node	10:15 am local solar time
ground resolution	16m at nadir
revisit time	4 days
swath width	>800km

Fig. 1. The GF-1 WFV imaging system (sensors image credit: DFH Satellite Co. Ltd., China).