Gradable Cloud Detection in Four-Band Remote Sensing Images

Shuwei Hou[1,2(✉)], Wenfang Sun[1], Baolong Guo[1], Xiaobo Li[2], and Huachao Xiao[2]

[1] School of Aerospace Science and Technology, Xidian University, Xi'an, People's Republic of China
hsw521@sina.com
[2] China Academy of Space Technology, Xi'an, People's Republic of China

Abstract. Cloud detection is one of the major techniques in remote sensing image processing. Many cloud detection algorithms have been developed recently. According to the type of remote sensing images that are used to detect cloud, they can be divided into two major categories: visible image-based methods and multispectral image-based methods. The first category mainly uses structure and texture characteristics for thick cloud detection, while the second category often uses the specific spectral bands for good results. In general, the existing methods above deal with cloud detection as a binary classification problem, cloud or non-cloud. However, as cloud has various forms and types, it is inappropriate to simply classify detection results into cloud or non-cloud. In this paper, we present a novel cloud detection method using orthogonal subspace projection (OSP), which can yield gradable cloud detection results. This detailed detection result not only conforms to the characteristics of cloud, but also brings more valuable guidance to subsequent interpretation of remote sensing images. Additionally, the proposed method only uses four universal bands including red, green, blue and near-infrared bands for detection, and has no requirement for special spectral bands, which make it more practical. Experiment results indicate that the proposed method has excellent results with high speed and accuracy.

Keywords: Remote sensing image · Cloud detection · Gradable

1 Introduction

Space imaging systems have the ability to collect digital images with high resolution and wide coverage of land surface. However, the captured rich information also brings great challenges to information storage, transmission, extraction and application. According to statistics, more than 50% of the optical remote sensing images are covered by clouds of different thickness, which consumes most transmitted time and link bandwidth, therefore affects the downlink priority of important information. Furthermore, cloud increases the difficulty in identifying important targets such as aircrafts and ships. Accordingly, the study of real-time cloud detection technology is of great significance for reducing data on-board and improving the intelligent processing ability of remote sensing images.

B. Li et al. (Eds.): IoTaaS 2018, LNICST 271, pp. 469–476, 2019.
https://doi.org/10.1007/978-3-030-14657-3_48

Cloud detection technology of remote sensing image has been one of the major techniques in remote sensing image processing. It can be summarized in two categories: visible image-based methods and multispectral image-based methods. The visible image-based methods include linear dimension compression for feature space [1] and multi-attribute fusion algorithm [2], etc. These methods mainly focus on how to effectively extract cloud features to achieve better cloud detection results.

Recently, carrying multispectral or hyperspectral imaging spectrometer [3] gradually become a development trend of satellite surveying approach, basically because it can provide remote sensing image processing with favorable conditions. Under this circumstance, multispectral image-based methods often use the specific spectral characteristics to detect cloud, of which the threshold, pattern classification and multi-dimensional space analysis methods are the most notable. The threshold method takes full advantage of the spectral characteristics of cloud, simple and easy to FPGA implementation, but relying on the specific spectrum to ensure the performance of the algorithm. The HCC algorithm [4] used on EO-1 satellite and the ACCA algorithm [5] used on Landsat-7 satellite, both select representative spectral bands to complete cloud detection. To improve the cloud detection result, some researchers use both the spectral and statistical features of cloud, and then use a classifier to separate clear and cloudy pixels. Reference [6] combined the texture features and spectral features of cloud with MODIS remote sensing data, followed by a neural network to complete detection. Generally the pattern classification method has better cloud detection results than the threshold method. However, it is more complex and more difficult to implement. Finally, the multi-dimensional space analysis method uses the signal processing principle to detect cloud. In [7], a cloud detection based on ICA is proposed, which is processed in higher space and has relatively large computation amount.

It turns out that many different methods generally deal with cloud detection as a binary classification problem. Cloud detection results are either cloud or non-cloud. However, as the form and type of cloud is various, it is not appropriate to simply classify the cloud detection results into cloud or non-cloud. Therefore how to further subdivide the cloud detection results to different levels of cloud products, is not only more accordant with the features of cloud, but also brings more valuable guidance to subsequent interpretation of remote sensing images. Although in [8], a multilevel cloud detection algorithm is proposed based on deep learning, it can only detect two levels of cloud, thick cloud and thin cloud, and also need more cloud samples corresponding to the two different levels, accordingly it increases the complexity of the algorithm.

In addition, most multispectral image-based methods are based on specific sensors, MODIS [11], Landsat or AVHRR [9, 10], etc., which cannot be widely used on different satellites. By contrast, four-band (red, green, blue, and near-infrared) remote sensing images are generally accessible and universal. Nearly all optical sensors such as those equipped on HJ-1a/1b, ZY-3 and GF series satellites can provide four-band remote sensing images. Although cloud detection in four-band remote sensing images is more general and applicable, it is too difficult to implement with its little spectral information. This paper focuses on orthogonal subspace projection for cloud detection in four-band remote sensing images. Our proposed algorithm not only can yield refined levels of cloud products, but also has low complexity.

In summary, the presented method has the following two main contributions.

(1) A gradable cloud detection approach is proposed. The new approach applied orthogonal subspace projection (OSP) to cloud detection and yields more detailed information about cloud thickness.
(2) The novel approach generalized the OSP algorithm from hyperspectral unmixing to cloud detection in four-band remote sensing images, which is more universal and practical.

The remainder of this paper is organized as follows. Section 2 introduces four-band cloud detection. Section 3 describes the experimental data, results and discussions. Section 4 analyzes the computation complexity and Sect. 5 draws the conclusion.

2 Four-Band Cloud Detection Based on OSP

Generally, input pixel can be seen as a mixed pixel with cloud contamination. Inspired by the OSP unmixing algorithm, we first introduced the concept of unmixing to cloud detection and tested its validity through experiments.

Different with hyperspectral unmixing problem, four-band cloud detection based on OSP has its difficulties and particularity. First, cloud has various forms and types, leading to the variability of the target subspace. Second, the spectral information of four-band (red, green, blue, and near-infrared) is much less than those in hyperspectral image. To solve these problems, our proposed algorithm is improved from two aspects: optimizing background subspace estimation and expanding cloud subspace. By using the improved OSP methods, graded cloud detection results can be generated for four-band remote sensing images.

2.1 Estimation of Background Subspace

In hyperspectral image processing, ATGP algorithm proposed by REN [13] can automatically generate the background with no required a priori knowledge. However, it is not ideal to directly apply the method to our four-band cloud detection because of the little spectral information. Furthermore, there is no guarantee that each generated signature is completely different from the desired target in the spectral characteristics, so leakage often happens from the cloud subspace to the background subspace.

As to the background generation of multispectral image, we proposed a multi-band automatic target generation process (MATGP) based on the ATGP algorithm. Followed by the background generation (ATGP), a false background removing processing is designed. The detailed implementation is given as follows.

Let the undesired background U generated by ATGP is

$$\mathrm{U} = [u_1\, u_2 \cdots u_i \cdots u_m]$$

where U is an L * m matrix and $u_i (1 \le i \le m)$ is the ith background signature.

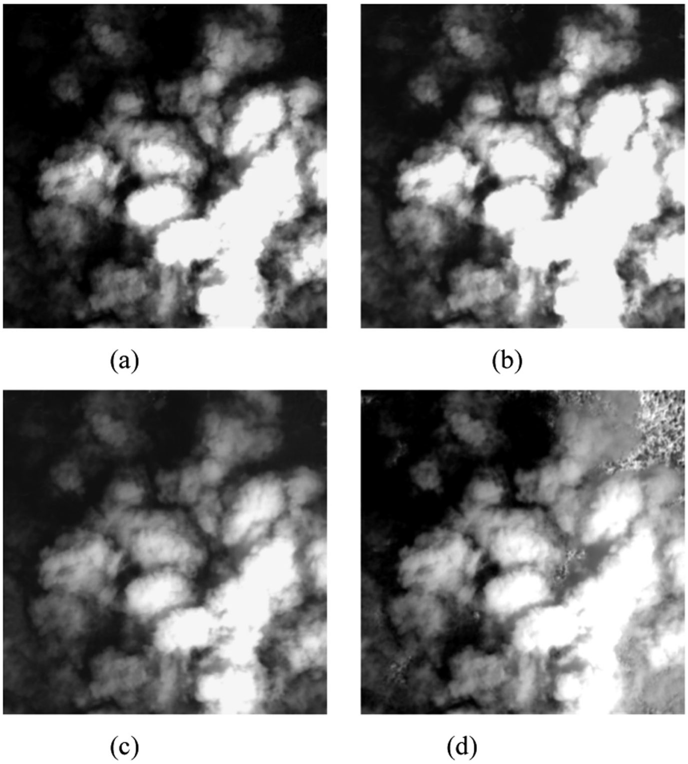
Let t be an L * 1 column vector and denote the desired target. Then the spectral similarity between t and u_i is given by

$$specoff_i(t, u_i) = \frac{t^T u_i}{\sqrt{t^T t} * \sqrt{u_i^T u_i}}$$

Let *Th* be a spectral similarity threshold. The removing processing is given as follow:

If $specoff_i$ is greater than *Th* then the corresponding background u_i is removed from <U>. Otherwise, the corresponding background u_i is preserved in <U>. Finally, the updated background is the true background with qualified conditions.

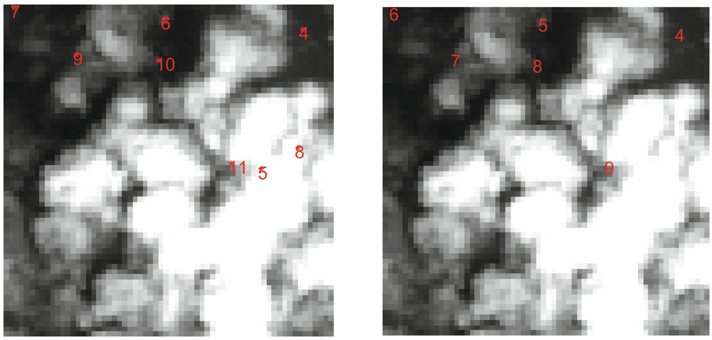
Figure 1 shows the four GF-1 bands labeled by (a)–(d). For the purpose of comparison, the maximum number of target required to search was all set to 11 to terminate the background generation. The ATGP result is shown in Fig. 2(a), where target labeled by 1–3 is of cloud subspace (cloud subspace is not shown here), and target labeled by 4–11 is of background subspace. It is clear that target 5 and target 8 are cloud-like targets and will result in the loss of cloud.



(a) (b)

(c) (d)

Fig. 1. Four-band images

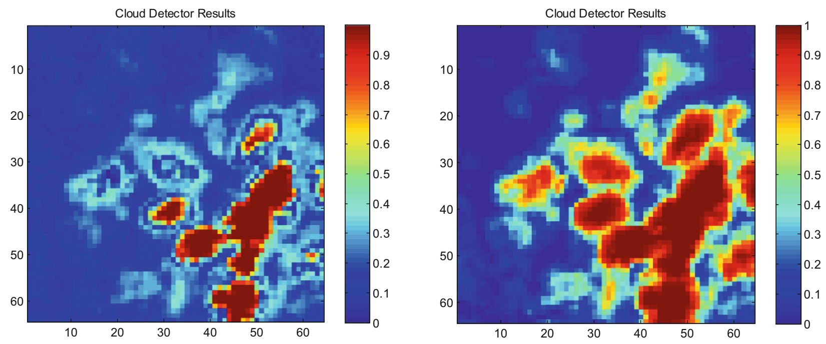


(a) (b)

Fig. 2. Search of background (a) ATGP background (b) our MATGP background

The MATGP result is shown in Fig. 2(b). It can be seen that cloud-like targets are all removed and the remaining is a good estimation of the background.

Figure 3 gives the corresponding cloud detection results with the above two different background estimation algorithm. Figure 3(a) used ATGP background search algorithm, which resulted in the loss of most cloud. Figure 3(b) used MATGP background search algorithm and yielded better results.



(a) (b)

Fig. 3. Cloud detection result (a) using ATGP background (b) using MATGP background

2.2 Estimation of Target Subspace

In the OSP algorithm, target t is generally known as a priori information. Usually, the target is modeled by extracting a single spectral signal. However, not only the type and forms of cloud are varied, but also the thickness and the height of cloud are different. Therefore, the spectral features of cloud exhibit significant variability. In order to improve the modeling of spectral characteristics of cloud, we expand cloud subspace from a single vector to P-dimension subspace ($P > 1$).

2.3 Adaptation of Four-Band Cloud Detection Based on OSP

In our four-band cloud detection, we only have 4 bands, whereas the total objects in remote sensing images are mostly larger than 4. Therefore we cannot distinguish all the objects by their spectral information. In other words, directly using OSP for our four-band cloud detection is not ideal. Under such circumstances, the number of bands must be expanded to meet the classification conditions [12]. In remote sensing images, less than ten objects are usually adequate to model any given areas of a given spatial resolution [14]. Here we extended the four-band remote sensing images to 18 bands.

3 Experiments

The four-band remote sensing images collected by GF-1 were used for experiments, which were blue band (0.45 μm–0.52 μm), green band (0.52 μm–0.59 μm), red band (0.63 μm–0.69 μm) and near-infrared band (0.77 μm–0.89 μm), with a spatial resolution of 8 m.

The following gives the experimental results with a wide range of GF-1 area. Figures 4, 5 and 6 show the original four-band images, the OTSU results and the gradable cloud detection results respectively. It can be found that our method not only detects the cloud regions accurately, but also provides more detailed information about

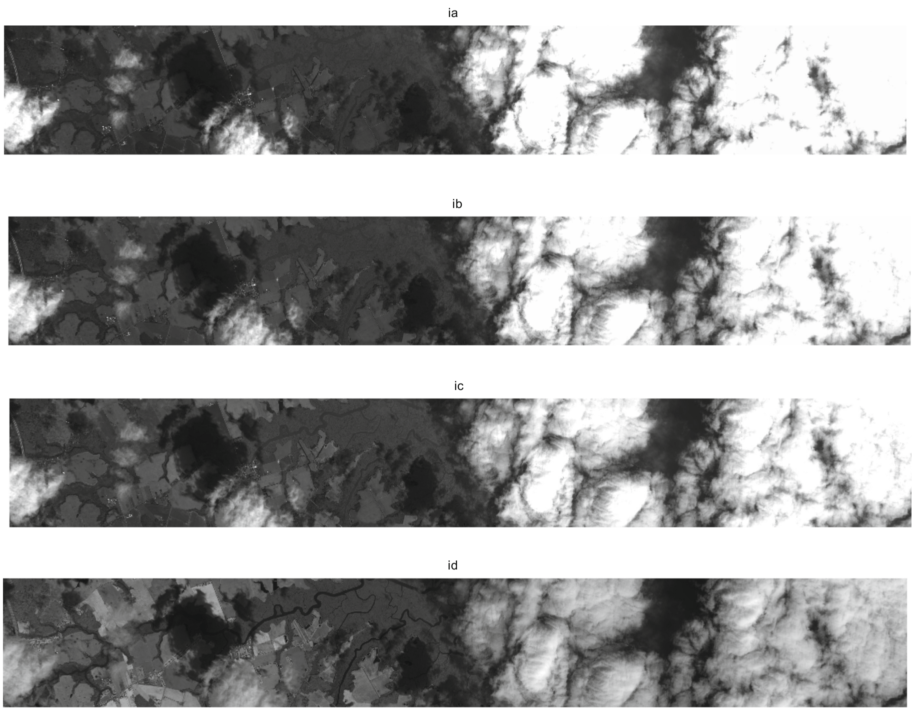


Fig. 4. Four-band images

cloud thickness. As is seen in Fig. 6, different color in the color bar illustrates different categories of cloud. For example, red areas represent thick clouds, yellow areas represent the edge of cloud, and light blue areas represent thin cloud, etc. At the same time, the scale values from high to low, in turn, indicate that the detected area is cloud, very likely to be cloud, may be cloud or non-cloud. The gradable cloud products can be more helpful for subsequent intelligent processing tasks (for example, cloud removal task [15] and ROI compression [16]).

Fig. 5. OTSU results

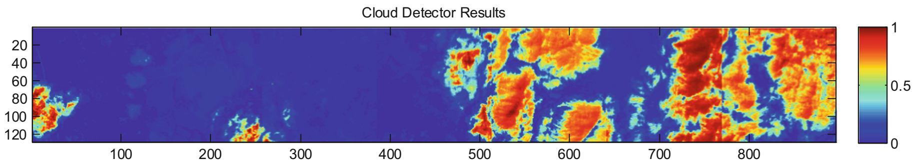


Fig. 6. Gradable cloud detection results (Color figure online)

4 Computation Complexity

In this paper, an OSP-based method is applied to detect cloud. In the algorithm, background U and cloud target t only need to be computed once. When real-time cloud detection is used on satellite, only multiplication and addition operations are implemented in the cloud detector. If the number of bands is L, our detector only needs L multiplications and L-1 additions for each pixel. As cloud detection in different pixel is independent of each other, multiple detectors can be used in parallel to speed up processing. Therefore, our method is a rapid cloud detection method with high degree of parallelism and very low computational complexity.

5 Conclusion

In this paper, a gradable cloud detection method in four-band remote sensing images is proposed. The method not only can yield gradable cloud detection results, but also has no requirement for special spectral bands. Moreover, it even has no strict limit on the number of bands. Therefore our method is more practical to satellite cloud detection. Our method has been tested on real remote sensing images with different scene, and the experimental results have proved its efficiency.

References

1. Bian, C., Hou, Q.: Cloud detection in remote sensing image based on linear dimension compression. J. Harbin Inst. Technol. **46**(1), 29–33 (2014)
2. Zhao, X., Hou, Q.: A method for cloud detection in high-resolution remote sensing image based on multi-attribute fusion. Opt. Tech. **40**(2), 145–150 (2014)
3. Feng, S., Zhang, N.: Method of cloud detection with hyperspectral remote sensing image based on the reflective characteristics. China Opt. **8**(2), 198–204 (2015)
4. Ricciardelli, E., Romano, F.: Physical and statistical approaches for cloud identification using meteosat second generation-spinning enhanced vision and infrared imager data. Remote Sens. Environ. **112**, 2741–2760 (2008). Science Direct
5. Williams, J.A., Dawood, A.S.: FPGA-based cloud detection for real-time onboard remote sensing. In: IELCONF (2002)
6. Song, X., Yingshi, Z.: Cloud detection and analysis of MODIS Image. Journal of Image and Graphics **8A**(9), 1079–1083 (2003)
7. Du, H., Wang, Y.: Studies on cloud detection of atmospheric remote sensing image using ICA algorithm. In: Image and Signal Processing Conference (2009)
8. Xie, F., Shi, M.: Multilevel cloud detection in remote sensing images based on deep learning. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. **10**(8), 3631–3639 (2017)
9. Saunders, R., Kriebel, K.T.: An improved method for detecting clear sky and cloudy radiances from AVHRR data. Int. J. Remote Sens. **9**, 123–150 (1987)
10. Bankert, R.L.: Cloud classification of AVHRR imagery in maritime regions using a probabilistic neural network. J. Appl. Meteorol. **33**, 909–918 (1994)
11. Ackerman, S., Strabala, K.: Discriminating clear-sky from clouds with MODIS. J. Geophys. Res. **103**, 141–157 (1998)
12. Ren, H., Chang, C.-I.: A generalized orthogonal subspace projection approach to unsupervised multispectral image classification. IEEE Trans. Geosci. Remote Sens. **38**(6), 2515–2528 (2000)
13. Ren, H., Chang, C.-I.: Automatic spectral target recognition in hyperspectral imagery. IEEE Trans. Aerosp. Electron. Syst. **39**(4), 1232–1249 (2003)
14. Adams, J.B., Smith, M.O.: Imaging Spectroscopy: interpretation based on spectral mixture analysis. In: Pieters, C.M., Englert, P.A. (eds.) Remote Geochemical Analysis: Elemental and Mineralogical Composition, pp. 145–166. Cambridge University Press, Cambridge (1993)
15. Gomez-Chova, L., Amoros-Lopez, J.: Cloud masking and removal in remote sensing image time series. J. Appl. Remote Sens. **11**(1), 015005 (2017)
16. Christine, M., Samuel, R.: A feasibility study of on-board cloud detection and compression. In: Aerospace Conference. IEEE (2010)