Cloud detection method for Pleiades images using spectral indices

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Abstract. Satellite images such as Pleiades have been widely used to monitor the earth. But there is a main issue regarding cloud cover which interferes the information of the images. Another issue is that there are very few studies discussing cloud detection for very-high-spatial-resolution such as Pleiades imagery. In this study, we proposed a cloud detection approach for Pleiades images to address these issues. In the first step, whiteness test was used to detect thick cloud. We also used modified HOT test in the second step to address the issue of detecting thin cloud. We modified the original HOT algorithm to decrease the omission error especially caused by thin cloud. We used visual assessments to evaluate the results. As a result, we found that cloud can be detected accurately by combining these algorithms. The results showed that the proposed approach can be used to detect cloud for Pleiades-1A images.

1. Introduction
Remote sensing satellite images have been widely used for many applications such as agriculture [1-3], forestry [4, 5], climate change [6], disaster monitoring [7-9], etc. Unfortunately, there is a serious issue to apply those applications i.e., cloud cover. Cloud interferes the information in the satellite image. it becomes more seriously as two third of the earth covered by cloud every year [10].

Manual digitization has been used to identify cloud by doing hand-drawing cloud polygons directly on the image. This approach provides an accurate result. However, it is difficult to apply this approach for a big number of images. In decades, many automated cloud detection methods have been developed to address the issue of cloud cover. It can be classified by two categories, i.e., single image based and multitemporal image based.

In single image based, an approach called Automated Cloud-Cover Assessment (ACCA) was developed to detect cloud for Landsat 4, 5, and 7 images [11]. Visible, near-infrared (NIR), shortwave-infrared (SWIR) and thermal-infrared bands were used in this approach to identify cloud. This automated approach can be used for a global area. Another method used single image based is Functional Mask (Fmask) developed by [12]. This approach is a popular algorithm in detecting cloud, cloud shadow and snow for Landsat 8 and Sentinel-2 images.

In multitemporal image based, Multitemporal Cloud Masking (MCM) was developed by [13] to detect cloud and cloud shadow for Landsat 8 and Sentinel-2 images. This approach used the advantages of multitemporal images to detect cloud and cloud shadow. This method can also be used for a variety of environments [14].
All methods were described above can be used for satellite images in medium resolution such as
Landsat and Sentinel-2. There are still few methods addressing the issue of cloud for very-high-spatial-
resolution satellite image. In this study, we proposed a cloud detection method for Pleaides.

Pleiades-1A satellite which has 0.5m high resolution satellite image was launched on December 16,
2011. It has four multispectral bands and a panchromatic band (see Table 1). The image swath is 20 km
at nadir and the data quantization is 12 bit per pixel. It is quite difficult to develop an algorithm for cloud
detection as it has only visible and NIR bands.

### Table 1. Spectral bands in Pleaides-1A

| Spectral bands       | Wavelength (nm) | Spatial resolution (m) |
|----------------------|-----------------|------------------------|
| Blue                 | 450-530         | 2.8                    |
| Green                | 510-590         | 2.8                    |
| Red                  | 620-700         | 2.8                    |
| Near infrared (NIR)  | 775-915         | 2.8                    |
| Panchromatic         | 480-820         | 0.7                    |

In this study, we proposed a cloud detection approach using spectral indices. We used a combining
test between whiteness test and modified (Haze Optimized Transformation) HOT test to detect cloud for
Sentinel-1A images. The original HOT algorithm was slightly modified to decrease the omission error
especially caused by thin cloud.

2. Material and method

2.1. Pleaides-1A images
In this study, we used Pleaides-1A images which has four multispectral bands and one panchromatic
band. We selected several Pleaides images which have different land covers to show that the proposed
method can be used to detect cloud in heterogeneous land cover. They can be seen in Figure 1.

![Figure 1. Pleaides images in heterogeneous land cover.](image)

2.2. Method
There are two main steps in the proposed method in detecting cloud. First, the whiteness index was
originally proposed by [15] is used to detect cloud especially thick cloud. This index uses visible bands
(see Equation (1)). In the equation, bands 1, 2 and 3 is blue band, green band and red band, respectively.
This whiteness index separates “white” and non “white” enough to be cloud. Therefore, the bright
objects such as bare soil and sand may detect as cloud [12].

$$\text{MeanVis} = \frac{(\text{Band 1} + \text{Band 2} + \text{Band 3})}{3}$$  \hspace{1cm} (1)

$$\text{Whiteness Test} = \sum_{i=1}^{3} |(\text{Band } i - \text{MeanVis})/\text{MeanVis}| < 0.7$$  \hspace{1cm} (2)

In the second step, the modified HOT test is used to detect haze and thin cloud. The HOT algorithm
firstly proposed by [16] for Landsat images. We slightly modified the original HOT algorithm in the
constant number. This modification can increase the accuracy of the proposed method in detecting cloud for Pleaides-1A.

\[ \text{HOT Test} = \text{Band 1} - 0.5 \times \text{Band 2} - 630 > 0 \]  

(3)

3. Results and Discussion

We selected four Pleaides images which have heterogeneous of land cover to evaluate the reliability of the proposed method. The results of cloud detection these images can be seen in Figure 2. The proposed method can detect thick cloud and thin cloud above forest area whereas very thin cloud failed to be detected by the method (see Figure 2(b)). We considered to keep very thin cloud as if we mask it, we will lose lots of the information of the data. On the other hand, in cropland area, the proposed method also successfully detected cloud (see Figures 2(d) and 2(f)). However, it failed to detect cirrus cloud (see Figure 2(f)). We also considered not to remove the cirrus cloud contaminated pixels as we prefer to keep them.

It is difficult to separate cloud to urban area because they have similar spectral response especially in the visible and near infrared bands. Hence, the results in this area still provided commission errors even though the errors are minor (see Figures 2(d) and 2(h)).
Figure 2. The results of cloud detection for Pleiades images in heterogeneous land cover.

4. Conclusions
The combining of the whiteness test and modified HOT test was used to develop a cloud detection method for Pleiades-1A images. As a result, the proposed method can detect cloud for Pleiades-1A images in heterogeneous land cover such as forest, cropland, open land, settlement and water successfully. The advantages of this method are automatic and fast in process. Therefore, it can support for a big dataset. This method keeps very thin cloud and cirrus cloud to minimize the loose of the information of the data. However, the lack of the thermal and shortwave infrared bands caused this method provided a commission error in terms of separating cloud to settlement. Therefore, this issue might be investigated and addressed in the further research.

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