New Cloud Detection Algorithm for Multispectral and Hyperspectral Images: Application to ENVISAT/MERIS and PROBA/CHRIS Sensors

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Abstract—This work presents a new methodology that faces the problem of accurate identification of location and abundance of clouds in multispectral images acquired by space-borne sensors working in the visible and near-infrared (VNIR) spectral range. The amount of images acquired over the globe every day by the instruments on board Earth Observation satellites makes inevitable that many of these images present cloud covers.

The objective of this work is to develop and validate a method that takes advantage of the high spectral and radiometric resolution, and the specific band locations (e.g. the oxygen band) of present multispectral sensors to increase the cloud detection accuracy. Moreover, the method provides probability and cloud abundance rather than flags, which can be used to describe detected clouds (subpixel coverage, cloud type, height, etc) more accurately.

I. INTRODUCTION

Accurate and automatic detection of clouds from remote sensing images is a key issue for a wide range of remote sensing applications, especially in the case of sensors working in the visible and near-infrared (VNIR) range of the electromagnetic spectrum. Without an accurate cloud masking, undetected clouds in the scene are a significant source of error in biophysical parameter retrieval over both sea and land covers [1]. The simplest approach to cloud detection in a particular scene is the use of a set of static thresholds (e.g. albedo or temperature) applied to every pixel in the image. These methods can fail for several reasons, such as subpixel clouds, high reflectance surfaces, illumination and observation geometry, sensor calibration, variation of the spectral response of clouds with cloud type and height, etc [1].

The common approaches for cloud detection heavily depend on the characteristics of each sensor. Obviously, its spectral and spatial resolution, or the spectral range are critical. For example, the presence of channels in the thermal infrared enables detection based on thermal contrasts [2], [3]. These sensors with spectral channels beyond 1 μm have demonstrated good capabilities to perform cloud masking, but this spectral range can not be exploited by recently developed multispectral sensors that work in the spectral range between 400-1000 nm. However, even in these cases, one can take advantage of their high spectral and radiometric resolution, and the specific band locations (e.g. the oxygen band) to increase the cloud detection accuracy, and to properly describe detected clouds [4]. In this context, the main goal of this paper is to develop a method for cloud detection using the full spectral information provided by multispectral sensors. The method must be capable of detecting clouds accurately providing probability and cloud abundance instead of flags. This information can be used to better describe clouds in order to include their properties (abundance, type, height, subpixel coverage) in radiation models [5].

In particular, performance of the presented approach is tested on images from two recent multispectral instruments with completely different characteristics: the MEdium Resolution Imaging Spectrometer (MERIS) instrument on board the European Space Agency (ESA) ENVISAT environmental satellite; and the Compact High Resolution Imaging Spectrometer (CHRIS) mounted on board the ESA small satellite platform called PROBA (Project for On Board Autonomy). Two of the key features of the MERIS instrument are its temporal resolution (revisit time of 3 days) and its spatial coverage (swath width of 1150 km), which make inevitable the presence of cloud covers. In full resolution (FR) mode, MERIS provides 300 m pixel-size images with 15 narrow bands, in the spectral range from 400 nm to 900 nm, at unprecedented spectral and radiometric resolutions. On the other hand, thanks to the PROBA platform pointing capabilities and small CHRIS spatial coverage, the acquisition plan of CHRIS tries to avoid acquisitions with cloud coverage, but from time to time images are partially affected by clouds. However, CHRIS sensor provides hyperspectral images (up to 62 channels) in the spectral range from 400 nm to 1050 nm with a maximum spatial resolution of 17 or 34 m at nadir depending on the acquisition mode. This high resolution makes CHRIS a good choice in order to propose and validate cloud detection methodologies.

II. CLOUD DETECTION ALGORITHM

The proposed cloud detection procedure uses as input data the multispectral image and, when available, the illumination...
and observation geometry information and a digital elevation model (DEM). Both MERIS and CHRIS products are provided in top of the atmosphere (TOA) radiance (radiometrically calibrated data). However, the method must work under many situations. Therefore, TOA reflectance is estimated to remove the dependence on particular illumination conditions (day of the year and angular configuration) and illumination effects due to rough terrain (cosine correction). TOA apparent reflectance is estimated according to:

\[
\rho(\lambda) = \frac{\pi \cdot L(\lambda)}{\cos(\theta_I) \cdot I(\lambda)},
\]

where \(L(\lambda)\) is the provided at sensor upward TOA radiance, \(I(\lambda)\) is the extraterrestrial instantaneous solar irradiance, and \(\theta_I\) is the angle between the illumination direction and the vector perpendicular to the surface.

Essentially, the cloud-detection algorithm is constituted by the following steps:

1) **Feature extraction:** physically-inspired features are extracted to increase separability of clouds and surface.

2) **Region of interest:** growing maps are built from cloud-like pixels in order to select regions which potentially could contain clouds.

3) **Image clustering and labeling:** an unsupervised clustering is applied to the extracted features and the resulting clusters are subsequently labeled into geo-physical classes according to their spectral signatures.

4) **Spectral unmixing:** a spectral unmixing is applied to the segmented image in order to obtain an abundance map of the cloud content in the cloud pixels.

### A. Feature Extraction

The measured spectral signature depends on the illumination, the atmosphere, and the surface. Spectral bands free from atmospheric absorptions contain information about the surface reflectance, while others are mainly affected by the atmosphere. Physically-inspired features that increase separability of clouds and surface covers can be extracted independently from the bands that are free from atmospheric effects and from the bands affected by the atmosphere.

Regarding the reflectance of the surface, a characteristic of clouds is that they present bright and white spectra.

- A **bright** spectrum means that the intensity of the spectral curve (related to the albedo) should present relatively high values. Therefore, cloud brightness is calculated as the integral of spectrum, \(\int \rho(\lambda) d\lambda\).

- A **white** spectrum means that the first derivative of the spectral curve should present low values. For the present method, the average of the spectral derivative, \(\langle d\rho(\lambda)/d\lambda\rangle\), has been chosen as one of the features.

Regarding the atmospheric absorptions present in the spectrum of a pixel, another meaningful feature is the fact that clouds are at a higher altitude than the surface. It is worth noting that atmospheric absorption depends on the atmospheric components and the optical path. Since light reflected on high clouds crosses a shorter section of the atmosphere, the consequence would be an abnormally short optical path, thus weaker atmospheric absorption features. Atmospheric oxygen or water vapour absorptions (at 760 nm and 940 nm respectively) can be used to estimate this optical path.

The light transmitted through a non-dispersive medium can be expressed by (Bouguer-Lambert-Beer law):

\[
L(\lambda) = L_0(\lambda) \cdot \exp(-\tau/\mu) = L_0(\lambda) \cdot \exp(-\tau(\lambda) \cdot d/\mu),
\]

where \(L_0(\lambda)\) is the initial light, the term \(\exp(-\tau/\mu)\) is the transmittance factor, \(1/\mu\) is the optical mass, \(\tau\) is the optical depth, \(\tau(\lambda)\) is the atmospheric optical depth for a vertical path, and \(d\) is a factor accounting for the path crossed by the radiation\(^1\). Assuming that there are no horizontal variations in the atmospheric component concentrations, one can consider that the optical path only depends on the height. Therefore, an estimation of the atmospheric absorption provides a measure of the optical path:

\[
d = \mu / \ln(L(\lambda)/L_0(\lambda)) \cdot \tau(\lambda),
\]

where the effective atmospheric vertical transmittance, \(\exp(-\tau(\lambda))\), is estimated for the channels of the instrument

\(^1d\) can be interpreted as a product of the component concentration and the distance crossed by the radiation that will be approximately 1 when the light crosses one atmosphere with a vertical path.
from a high resolution curve; and the spectral signature without absorption, \( L_0(\lambda) \), is estimated by interpolating the nearby channels that are unaffected by this absorption. The approach followed in this paper can be devised from Fig. 1 for the so-called Oxygen-A band. However, a short optical path can also be obtained over high altitude locations since light crosses lower portion of atmosphere when is reflected at a high mountain and low values of \( d \) are found. Therefore, when a DEM is available, the quality of the extracted features can be improved by removing topographic effects. In this process, we neglect dependence on the temperature and the pressure since the objective is not an accurate or unbiased height estimation but a good relative measure for cloud detection.

B. Region of interest

The set of representative features for the cloud detection problem is extracted in order to improve the segmentation of the image. In addition, the results of the clustering algorithm will also improve when applied over the regions of the image where clouds are statistically representative. In order to find regions that potentially could contain clouds, hard non-restrictive thresholds are used to provide a first map of cloud-like pixels. Then, a region growing algorithm is carried out, along with a morphological process that dilates cloudy areas. The result is not intended to be a classification, but to obtain a mask or region of interest (ROI), in which presence of clouds is significant for the later clustering.

C. Image Clustering and Labeling

The clustering algorithm is applied only to the selected ROI. The inputs for each pixel, \( x_i \), are the extracted features: the brightness in the VIS and the NIR region, the mean spectral derivative of the TOA reflectance, and the estimated oxygen and water vapour absorptions. We use the Expectation-Maximization (EM) algorithm [6] to estimate the parameters of a Gaussian mixture model since it considers the full relationship among variables and provides probability maps for each cluster. If the ROI has been correctly found, even using a low number of clusters, \( N \), some of them should correspond to different cloud types.

Once clusters are determined, the spectral signature of each cluster, \( s_i(\lambda) \), is estimated as the average of the spectra of the cluster pixels. At this point of the process, the obtained clusters can be labeled into geo-physical classes taking into account three complementary sources of information: the thematic map with the spatial distribution of the clusters in the scene, the spectral signatures of the clusters, \( s_i \), and the location in the image of the pixels with the spectral signature closer to \( s_i \). This information can be either analyzed directly by the user or compared to a spectral library with representative spectra of all the classes of interest.

Once all clusters have been related to a class with a geo-physical meaning (Fig. 2), or at least they have been classified as cloud or non-cloud, it is straightforward to merge all the clusters belonging to a cloud type. Since the EM algorithm provides posterior probabilities \(^2\) \( (P_{ik} \in [0, 1] \text{ and } \sum_{i=1}^{N} P_{ik} = 1) \), a probabilistic cloud index, based on the clustering of the extracted features, can be computed as the sum of the posteriors of the cloud-clusters: Cloud Probability \( k = \sum_i P_{ik} \) for all cluster \( i \) classified as cloud (Fig. 2).

D. Spectral Unmixing

In order to obtain a cloud abundance map for every pixel in the image, rather than flags or a binary classification, a spectral unmixing algorithm \(^3\) is applied to the multispectral image using the full spectral information. In our case, we are going to consider the spectral signatures of the clusters, \( s_i \), as the representative pixels of the covers present in the scene.

The vector \( a_k \) contains, for the sample pixel \( k \), the abundances of the spectral signatures of the clusters, which are related to a class with a geo-physical meaning. As it happens with the probabilities of the clusters, the abundance of cluster \( c_i \) for the pixel \( k \) is \( a_{ik} \in [0, 1] \) and \( \sum_{i=1}^{N} a_{ik} = 1 \). Therefore, the abundance of cloud is computed as the sum of the abundances of the cloud-clusters: Cloud Abundance \( k = \sum_i a_{ik} \) for all cluster \( i \) classified as cloud (Fig. 2).

\(^2\)The posterior probability of cluster \( c_i \) given the sample \( x_k \) is given by the Bayes theorem by \( P(i|x_k) = \frac{p(x_k|i)P(i)}{p(x_k)} \), where \( P(i) \) is the a priori probability of cluster \( c_i \).

\(^3\)The spectral unmixing algorithm expresses each pixel of the image, \( \rho_k \), as a linear combination of a set of basis vectors, \( M \), being the coefficients, \( a_k \), of this combination, \( \rho_k = M \cdot a_k \), the unmixing coefficients, which can be interpreted as the abundances of the spectral components expressed in \( M \) (usually called endmembers).
An improved cloud abundance map can be obtained when combining the Cloud Abundance and the Cloud Probability by means of a pixel-by-pixel multiplication. That is, combining two complementary sources of information processed by independent methods: the degree of cloud abundance or mixing (obtained from the spectra) and the cloud probability that is close to one in the cloud-like pixels and close to zero in remaining areas (obtained from the extracted features).

III. RESULTS

The proposed method was tested on a set of MERIS Full Resolution Level1b and CHRIS Mode1 products. In order to validate the performance of the method, the selected images represent scenarios with different characteristics: geographic location (lat/lon); date and season; type of cloud (cumulus, cirrus, stratocumulus); and surface types (water, soils covered by vegetation or bare, and two critical cases given the especial characteristics of the induced problems: ice and snow).

As no ground truth is available, we could merely analyze the performance of the proposed method by visual inspection. However, in the case of MERIS, we can also compare results with the official MERIS Level 2 Cloud Flag. Fig. 3 shows a case example result for an image over France that presents a critical problem associated with cloud detection: snowy mountains at various altitudes (Pyrenees, Massif Central, and Alps). Two main differences can be found with the MERIS Level 2 Cloud Flag. On the one hand, when our algorithm detects more cloudy pixels (red pixels), good agreement with cloud borders can be seen. Therefore, one can assume that the proposed method provides better recognition in cloud borders and in small and thin clouds. On the other hand, differences when our algorithm classify as cloud free are shown in yellow, and one can see that these areas correspond only to ice covers and snow over high mountains. Certainly, the presence of bright pixels is one of the critical issues in cloud detection (e.g. ice/snow in the surface), since these pixels and clouds have a similar reflectance behavior. However, the atmospheric absorption suffered by cloud pixels is lower than for the surface pixels due to their height, and results show that different clusters are identified for these two classes in the image. Thanks to the extracted atmospheric features, ice/snow pixels present low Cloud Probability values (provided by the clustering in the feature space) although the Cloud Abundance (provided by the spectral unmixing) could be relatively high due to the spectral similarities. In consequence, both information types are combined improving the final detection accuracy.

IV. CONCLUSIONS

This work presented a new technique that faces the problem of accurately identifying the location and abundance of clouds in multispectral images. Results has demonstrated that the proposed algorithm classifies difficult cloud pixels more accurately, especially thin cirrus clouds and clouds over ice/snow. One critical feature for the improved results was the use of the atmospheric oxygen and water vapour absorption bands together with an overlapped DEM. In the case of CHRIS, the oxygen band was not so useful because of its broader bandwidths. In case of MERIS, the maximum water vapour absorption (940 nm) is located outside the MERIS range but it is still valid for relative measurements inside the same image. Moreover, MERIS products allow us to take advantage of the illumination and observation geometry, an overlapped DEM, and an accurate oxygen absorption estimation. In any case, this procedure can serve to develop a cloud detection algorithm for other spectral sensors in the VNIR spectral range.

REFERENCES