CLOUD DETECTION FOR MERIS MULTISPECTRAL IMAGES

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ABSTRACT

Two of the key features of the MEdium Resolution Imaging Spectrometer (MERIS) instrument on board the ESA Envisat environmental satellite are its temporal resolution of three days and its spatial coverage. The amount of images acquired over the globe every day makes inevitable that many of these images present cloud covers. From an operational point of view, an automatic and accurate method for cloud detection in MERIS scenes is a key issue since, with no accurate cloud masking, undetected clouds are the most significant source of error for true ground reflectance, affecting a wide range of remote sensing applications. By masking only the image areas affected by cloud covers, the whole image is not necessarily discarded.

The main objective of this work is to develop and validate a method for cloud detection using self-contained information provided by MERIS Full Resolution Level 1b products and a Digital Elevation Model (DEM). The method must be capable of: detecting clouds accurately providing probability and cloud abundance rather than flags; and better describing detected clouds (cloud abundance, type, height, subpixel coverage) in order to include this information in radiation models.

Key words: cloud detection, cloud masking, multispectral images, MERIS, unsupervised classification, spectral unmixing.

1. INTRODUCTION

Accurate and automatic detection of clouds in satellite scenes is a key issue for a wide range of remote sensing applications. Clouds significantly affect the heat fluxes of the atmosphere and constitute one of the most important transient phenomena to be incorporated into climate models. Moreover, without an accurate cloud masking, undetected clouds in the scene are a significant source of error in both sea and land cover biophysical parameter retrieval [1].

The simplest approach to cloud detection in a scene is the use of a set of static thresholds (albedo, temperature) applied to every pixel in the image. These methods can fail for several reasons, such as sub-pixel clouds, high reflectance surfaces, illumination and observation geometry, sensor calibration, variation of the spectral response of clouds with cloud type and height, etc [1]. Spatial coherence methods have an advantage over static threshold methods because they use the local spatial structure to determine cloud free and cloud covered pixels [1]. However, spatial coherence methods can fail when the cloud system is multilayered (which often is the case), the clouds over the scene are smaller than the instrument spatial resolution, or the scene presents cirrus clouds (which are not opaque). As a consequence, researchers have turned to developing adaptive threshold cloud-masking algorithms [2].

The approaches for cloud detection and masking 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 [3, 4]. Optical sensors with spectral channels beyond 1 µm have demonstrated good capabilities to perform cloud masking. Some other recent hyperspectral sensors can not exploit this spectral range, such as the MEdium Resolution Imaging Spectrometer (MERIS) instrument on board ESA Envisat environmental satellite. However, one can take advantage of the high spectral and radiometric resolution, and the specific band locations to increase the cloud detection accuracy, and to properly describe detected clouds [5].

In this context, the main objective of this paper
is to develop and validate a method for cloud detection using self-contained information provided by MERIS Level 1b products and a Digital Elevation Model (DEM). The method must be capable of: detecting clouds accurately providing probability and cloud abundance instead of flags; and better describing detected clouds (cloud abundance, type, height, subpixel coverage) in order to include this information in radiation models [6].

2. DATA MATERIAL

A dataset consisting of four acquisitions over three sites has been selected since both Level 1b and Level 2 products were available for all MERIS Full Resolution (FR) images (300 m). In particular, the site of Barrax (BR, Spain) was selected as the main test site since it has been the core site of previous Earth observation campaigns and the analyzed cloudy images are part of the data acquired in the framework of the SPARC 2003 and 2004 ESA campaigns (ESA-SPARC Project, contract ESTEC-18307/04/NL/FF). These two images were acquired the same day of two consecutive years (July 14th, 2003 and 2004). Additionally, a set of MERIS/AATSR sample products taken over France (FR) and Finland (FI) have been included in the study in order to take into account their different characteristics: geographic location (latitude/longitude); date and season; type of cloud (cumulus, cirrus, stratocumulus); and surface types (soil, vegetation, sand, ice, snow, rivers, sea, etc.). The selected images represent different scenarios very useful to validate the performance of the method, including different landscapes; soils covered by vegetation or bare; and two critical cases given the especial characteristics of the induced problems: ice and snow.

Although the proposed method can be applied on the top of aerosols reflectance provided in Level 2 products, it is only applied to the MERIS Level 1b products (top of atmosphere radiances) because Level 2 products are processed from Level 1b using a cloud pixel classification that could be inaccurate. Therefore, Level 2 products are only used for validation purposes by comparing its cloud flag product with the cloud mask produced by the presented method.

3. IMAGE PRE-PROCESSING

Since the method must be general and must work under many situations, image information format must be homogeneous and with accurate data for all images. Therefore, in order to remove the dependence on particular illumination conditions (day of the year and angular configuration) and illumination effects due to rough terrain (cosine correction), Top Of Atmosphere (TOA) apparent reflectance is estimated according to [7]:

\[ \rho(\lambda) = \frac{\pi \cdot R(\lambda)}{\cos(\theta_S) \cdot S(\lambda)}, \]  (1)

where \( R(\lambda) \) is the provided at sensor upward TOA radiance, \( S(\lambda) \) is the extraterrestrial instantaneous solar irradiance, and \( \theta_S \) is the angle between the illumination vector and a vector perpendicular to the surface. In this work, \( \theta_S \) is computed for each pixel using the Sun Azimuth and Sun Zenith angles (provided in the Tie Point Location and Auxiliary Data of the MERIS product) and the vector perpendicular to the surface, which is computed from the GETASSE30 DEM (included in the BEAM ESA software). The Sun irradiance, \( S(\lambda) \), is taken from Thuillier et al. [8], corrected for the day of year when the acquisition takes place, and convolved with the MERIS spectral channels. (Fig.1).

Finally, one of the key features extracted from MERIS in this work is obtained from the oxygen absorption band that is extremely narrow. Therefore, before obtaining the TOA reflectances, in order to correct small variations of the spectral wavelength of each pixel along the image (smile effect), the BEAM Smile Correction Processor was used to calculate corrected radiances from the MERIS L1b products.

4. CLOUD DETECTION ALGORITHM

In this work, we present a cloud detection procedure which is constituted by the following steps:

1. Feature extraction: physically-inspired features are extracted to increase separability of clouds and any-other surface type.

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: an unsupervised clustering algorithm is applied using all extracted features in order to obtain all the existing clusters over the previously identified areas providing a probabilistic membership of pixels to each cluster.

4. Cluster labeling: the obtained clusters are labeled into geo-physical classes taking into account the spectral signature of the cluster centers, which allows to merge all the cloud-clusters providing a probabilistic cloud index.

5. Spectral unmixing: an spectral unmixing algorithm is applied to the segmented image in order to obtain an abundance map of the cloud content in the cloud pixels.
4.1. 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. Therefore, a series of considerations have been taken into account, as it is explained in the following paragraphs. For illustration purposes, the figures of this section will show maps of the extracted features from one of the images (BR-2003-07-14).

Regarding the reflectance of the surface, one of the main characteristics 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) must present relatively high values. Therefore, cloud brightness is calculated as the squared sum of spectral bands normalized by the number of bands. Bands that correspond to severe atmospheric absorptions are not included in order to consider only the target, thus avoiding atmospheric absorption effects. Considering the intensity independently in the VIS and NIR ranges discriminates clouds better since the rest of the surfaces have less reflectance in the VIS range (Fig.2).

- A white spectrum means that the first derivative of spectral curve must present low values. As previously discussed, bands on atmospheric absorptions are not included in order to consider only the surface contribution. Noise or calibration errors may reduce the accuracy in the estimation of the spectrum flatness. Smoothing or average ratios between the VIS and NIR can be more robust. For the present method, the mean spectral derivative has been chosen as one of the features (Fig.2).

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 may be used to estimate this optical path.

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

$$\rho(\lambda) = \rho_0(\lambda) \cdot \exp(-k(\lambda) \cdot d), \quad (2)$$

where the term \(\exp(-k(\lambda) \cdot d)\) is the transmittance factor; \(k(\lambda)\) is the atmospheric optical depth for a vertical path; and \(d\) is a factor accounting for the path crossed by the radiation (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).

Assuming that there are no horizontal variations in the atmospheric component concentrations, one can consider that the optical path only depends on the
altitude. Therefore, a robust estimation of the atmospheric absorption in the so-called Oxygen-A band provides a measure of the optical path. Even though MERIS has two specific spectral bands in this region (bands 10 and 11), estimating the optical path, $d$, is not straightforward. The approach followed in this paper can be devised from Fig. 3. Since the O$_2$ absorption band is extremely narrow, the effective atmospheric vertical transmittance, $k(\lambda)$, is estimated for the MERIS channels from a high resolution curve. The spectral signature without absorption, $\rho_0(\lambda)$, is estimated by interpolating the nearby samples that are unaffected by this process. Finally, the ratios between the interpolated and the measured reflectance at the affected bands provided by the instrument ($\lambda_i$) are used to estimate $d$.

$$d = \text{average} \left( -\frac{\ln(\rho(\lambda_i)/\rho_0(\lambda_i))}{k(\lambda_i)} \right)$$  

(3)

However, a short optical path can be obtained over high altitude locations (light crosses less atmosphere when is reflected at a high mountain and low values of $d$ are found). Therefore, when a good DEM is available, the extracted features can be improved by removing topographic contributions with an empirical model. Considering only the cloud free pixels, the optical path, $(1-d)$, can be related to the DEM in order to assess the real altitude of targets for a posterior removal of topographic effects (see details in Fig. 4), thus obtaining relative measurements to the surface (approximately zero in cloud free pixels). 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.

An additional estimation of the optical path can be obtained from the water vapour absorption in the NIR close to the end of the valid range of the sensor (900 nm). In this case, the maximum water vapour absorption (940 nm) is located outside the MERIS range and the water vapour distribution is extremely variable, thus it is not straightforward to relate this feature to the real altitude. However, it is still valid for relative measurements inside the same image since almost all the atmospheric water vapour is distributed in the first 2-3 km of the atmosphere below most of the cloud types. Moreover,
4.2. Region of interest

As previously discussed, static thresholds applied to every pixel in the image can fail due to sub-pixel clouds, sensor calibration, variation of the spectral response of clouds with cloud type and height, etc. On the other hand, unsupervised segmentation methods can find clusters of similar pixels in the image but direct relation of clusters with desired classes (e.g. clouds) is not ensured. In order to mitigate this drawback, in section 4.1, features have been extracted to increase separability of clouds from any-other surface type. Moreover, if clouds were not statistically representative in a given image, clustering methods could not find small clouds or could mix them with other similar classes. Therefore, in addition to using representative features, clustering improves if it is only applied over the regions of the image where clouds are statistically representative.

In order to find these regions that potentially could contain clouds, hard non-restrictive thresholds are used to provide a first map of cloud-like pixels. These absolute thresholds were obtained empirically and were applied to well-defined 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 [9] since it considers the full relationship among variables and provides probability maps for each cluster when subsequently applying a Gaussian Maximum Likelihood (GML) classifier. If the cloud ROI has been correctly found, even using a low number of clusters, some of them should correspond to different cloud types.

Once clusters are determined, the spectral signature of each cluster, \( \mathbf{s}_c(\lambda) \), is estimated as the average of the spectra of the cluster pixels but excluding those with abnormally low membership values (posterior probability \( P_{ik} \)). It is important to emphasize that these spectral signatures of each cluster could differ a lot from the spectra obtained when applying the EM algorithm over the image using the spectral bands rather than the extracted features. The extracted features used to find the clusters are optimized to increase separability between clouds and any-other surface type while in the spectral domain these clusters could present a high degree of overlap.

At this point of the process, the obtained clusters can be labeled into geo-physical classes taking into account three complementary sources of information (Fig.6): the thematic map with the distribution of the clusters in the scene, the spectral signatures of the cluster, \( \mathbf{s}_c \), and the location in the image of the pixels with the spectral signature closer to \( \mathbf{s}_c \). 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.7), it is straightforward to merge all the clusters belonging to a cloud type. Since the EM algorithm provides posterior probabilities\(^1\) \( P_{ik} \in [0, 1] \) 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 \( \mathbf{k} \) is \( \sum P_{ik} \) \( \forall i \) classified as cloud. However, if the clusters are well separated in the feature space, the posteriors decrease drastically from one to zero in the boundaries between clusters (Fig.7). Therefore, this Cloud Probability index indicates the probability that one pixel belongs more to a cloud-cluster than to one of the other clusters found in the image, but it does not give information about the cloud content at subpixel level (very important when dealing with thin clouds or partially covered pixels).

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\(^1\)The posterior probability of cluster \( c_i \) given the sample \( x_k \) is given by the Bayes theorem by \( P(\mathbf{i} | x_k) = \frac{P(x_k | \mathbf{i}) P(\mathbf{i})}{P(x_k)} \), where \( P(\mathbf{i}) \) is the a priori probability of cluster \( c_i \).
4.4. 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 \(^2\) is applied to the MERIS 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, and they are used to build matrix \(M\). The Fully Constrained Linear Spectral Unmixing (FCLSU) \(^1\) algorithm is used to perform the spectral unmixing. This algorithm solves a constrained linear least-squares problem minimizing the norm of \((M \cdot \mathbf{a}_k - \rho_k)\) where the vector, \(\mathbf{a}_k\), of independent variables is restricted to being nonnegative (since it represents the abundances or contributions of reflectance spectral signatures) and its sum being one (since it is supposed that \(M\) contains at least one spectrum for all the compounds in the image). If the ROI where the clusters were found did not cover the whole image, but the abundance map for all the image has to be obtained, it is necessary to include in \(M\) some representative pixels of the non analyzed areas by performing a clustering in these areas outside the ROI. Otherwise, the assumption that motivates the second constraint of the FCLSU algorithm can be false if there are new non-considered spectral classes outside the ROI, providing misleading abundances in these areas due to the high residuals \((M \cdot \mathbf{a}_k - \rho_k)\).

\(^2\)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, \(\rho_k = M \cdot \mathbf{a}_k\), the unmixing coefficients, which can be interpreted as the abundances of the spectral components expressed in \(M\) (usually called endmembers).

The vector \(\mathbf{a}_k\) contains the abundances of the spectral signatures of the clusters, which are related to a class with a geo-physical meaning, for the sample pixel \(k\). As it happens with the probabilities of the clusters, the abundance of cluster \(c_i\) for the sample \(k\) 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: \(\text{Cloud Abundance}_k = \sum a_{ik} \forall i \text{ classified as cloud}\) (Fig. 7). As in the case of the probabilities a threshold of 0.5 would give a good cloud mask, but some false detections could appear since the unmixing has been performed on the basis of spectral signatures that could be non-pure pixels or non completely independent.

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. In this way, we combine two complementary sources of information processed by independent methods: the degree of cloud abundance or mixing (obtained from the spectral information) 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).

5. RESULTS

The presented method was tested in a previous work [11] on CHRIS/Proba hyperspectral images in order to propose and validate cloud detection methodologies. The use of this data allowed us to assess algorithm performance in favorable spatial resolution (34 m) and number of bands (62 channels). However, MERIS products allow us to take advantage of: the illumination and observation geometry, an overlapped DEM, and an accurate oxygen absorption estimation. In this section, results of the proposed scheme for the aforementioned images will be shown. The by-pass images have been shown in the previous section (Fig.2 to Fig.7), and now we will analyze its performance by comparing the final clustering classification and cloud abundance product with the RGB composite of the MERIS images and the MERIS Level 2 Cloud Flag respectively (Fig.8).

The two images over the Barrax (Spain) site are a good example of an easy cloud detection problem, when dense clouds are well contrasted with soil and vegetation. The ROI selection can be easily appreciated in the classification images, being more important in the 2004-07-14 image where small clouds cloud be mixed in a cluster with other classes if the whole image is considered. At the 2003-07-14 image, dry soil pixels belong to a cluster labeled as cloud due to their high reflectance and whiteness, but they present low probabilities and abundances. The 2004-07-14 image presents thin and small clouds over land and over sea, which are well detected since a specific cluster describe them. One of the weak points of the algorithm is the use of thresholds to select the ROI, because some thin or small clouds can be excluded from the ROI. A possible solution for this is to relax thresholds at the risk of considering the whole image as ROI. But, even in this case, results are good if clouds cover a sufficient percentage of the image or the number of clusters is high enough (as in the image of Finland). 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 different clusters are found for these two classes in the image. Thanks to the extracted atmospheric features, ice/snow pixels present low Cloud Probability values 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 classification accuracy.

Finally, figures in last column of Fig.8 show a comparison of MERIS Level 2 Cloud Flag with the results from our algorithm. Pixels where both algorithms agree are in white for the cloudy pixels and blue for the cloud free pixels. From the results, two main discrepancies can be found. On the one hand, when our algorithm detects cloudy pixels they are plotted in red, showing a good agreement with cloud borders. Therefore, one can assume that the proposed method provides better recognition in cloud borders and in small and thin clouds. On the other hand, discrepancies when our algorithm classify as cloud free are shown in yellow, and one can see that these areas correspond only to ice covers (Finland image) and snow over high mountains (Pyrenees and Alps in the France image) indicating the goodness of our approach.

6. CONCLUSIONS

This work presents a new technique that faces the problem of accurately identifying the location and abundance of clouds in multispectral images. The proposed algorithm has demonstrated a clear improvement in the classification of hard-to-detect cloud pixels in ENVISAT MERIS FR images, especially thin cirrus clouds, and clouds over ice/snow. One critical feature for the improved results was the use of the O$_2$ and H$_2$O absorption bands together with an overlaped DEM, therefore it would be advantageous to see those bands included in future sensors. In any case, the procedure can serve as a test to develop a cloud masking algorithm for other spectral sensors of the VNIR spectral range.

Further refinements can be introduced in order to enhance the robustness of the procedure:

- using dynamic thresholds could be useful to find the regions to analyze;
- final maps could be further analyzed through texture algorithms;
- sun position could be taken into account in order to relate cloud and shadow positions, by detecting edges of the clouds and shadow regions, and then apply morphology operators that extract information on the structure of the image;
- DEM could be used together with the obtained cloud mask to correct the image and estimate cloud heights;
- coastline map could be used in order to improve results by considering clouds over land or water, separately.
Figure 8. MERIS images over the test sites of BR-2003-07-14, BR-2004-07-14, FI-2005-02-26, and FR-2005-03-19 displayed in rows from left to right. First row: RGB composite with an histogram stretching such that 10\% of data is saturated at both low and high reflectance (10\%-90\%) in order to increase the contrast of the cloudy images. Second row: Classification of the relevant regions. Third row: Cloud abundance product. Fourth row: Comparison of MERIS Level 2 Cloud Flag with the obtained cloud mask (discrepancies are shown in red when our algorithm detects cloud and in yellow when pixels are classified as cloud free).

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REFERENCES


