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Use of Markov Random Fields for automatic cloud/shadow detection on high resolution optical images

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ABSTRACT

In this study, we propose an automatic detection algorithm for cloud/shadow on remote sensing optical images. It is based on physical properties of clouds and shadows, namely for a cloud and its associated shadow: both are connex objects of similar shape and area, and they are related by their relative locations. We show that these properties can be formalized using Markov Random Field (MRF) framework at two levels: one MRF over the pixel graph for connexity modelling, and one MRF over the graph of objects (clouds and shadows) for their relationship modelling. Then, we show that, practically, having performed an image pre-processing step (channel inter-calibration) specific to cloud detection, the local optimization of the proposed MRF models leads to a rather simple image processing algorithm involving only six parameters. Using a 39 image database, performance is shown and discussed, in particular in comparison with the Marked Point Process approach.

1. Introduction

High resolution optical remote sensing images (such as SPOT/HRVIR) are often affected by cloud presence. For surface studies such as vegetation monitoring, change detection or land cover/land use analysis, these clouds appear either as some noise or some erroneous measurements that conceal or distort the information corresponding to the surface. Moreover, even if they represent only a small percentage of the scene surface, this proportion may be not negligible with regard to the rate of the studied phenomena, such as the land cover change. Hence, even if it is generally not possible to retrieve the missing data, it is important to identify the clouds and their shadows in order to not consider their signals on the studied area.

A large number of cloud detection methods have already been proposed. However, these methods are generally dedicated to data with spatial resolution of about one kilometer square, such as the NOAA/AVHRR images. Indeed, these approaches are based on the high temporal (Cihlar and Howarth, 1994) and spectral (Rossow and Garder, 1993; Chen et al., 2002) resolutions of that kind of data. Dealing with higher spatial resolution, the fourth component of the 'Tasseled Cap' transform (Kauth and Thomas, 1976) was found to be a good indicator of the presence of mist or clouds (Richter, 1996). However, this orthogonal transformation of the spectral bands is not optimized for cloud detection, since it was developed to distinguish the radiometric contribution of vegetation from those of bare soil. Then, recent work (Zhang et al., 2002) proposed an extension to derive a mist indicator and perform pixel radiometric correction. Concerning the shadow detection, different approaches have also been proposed. Some are based on the projection of the cloud shapes on the surface knowing the sun direction and the cloud altitude (Simpson and Stitt, 1998). Other approaches exploit the matched filter concept (Richter and Muller, 2005). The matched filter is then evaluated using the spectral band covariance matrix. Once more when the aim is the correction of the radiometric signal, previous methods are exploited in collaboration with a radiative transfer model. Finally, Ho and Zhenlei (1996) proposed comparing clouds and shadows to perform mutual validation of their detections.

Our work exploits several of the previously presented ideas. They were adapted and combined in order to derive a cloud/shadow detection method which is both robust and automatic. Relatively to classical threshold techniques, the proposed method exploits three main features of clouds (and shadows):

- P1: Clouds and shadows are connex objects;
- P2: Knowing the geometry of the acquisition and the sun location, the image location of the shadow of a cloud is known, but for one parameter (the cloud altitude);
- P3: Each cloud and its associated shadow have the same shape and area (but for the deformations due to relief).

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In this study we show that these properties (P1, P2, and P3) can be formalized using Markov Random Field (MRF) framework at two levels: one MRF over the pixel graph for P1 modelling, and one MRF over the graph of objects (clouds and shadows) for P2 and P3. In the case of the object MRF, the graph nodes represent the objects, whereas the graph edges model the interactions between objects. Hence, this approach assumes the a priori knowledge of the number of objects and their interactions. Practically, this implies an initial over-detection of clouds and shadows that may have an impact on the final result. Therefore we have compared our approach to a model in which the number of objects and relationships between objects may be a priori unknown, namely the Marked Point Processes (MPP). However, this last approach is also much heavier in terms of optimization process and computation time. Besides, since it uses a global optimization, it demands the precise setting of the model parameters, whereas the local optimization of our first model (MRF) allows avoiding such a fastidious process.

The rest of the article is organized as follows. Section 2 presents the considered SPOT/HRVIR image features and database acquired in the AMMA (African Monsoon Multidisciplinary Analysis) program framework. Section 3 presents the model based on MRF (whereas MPP main concepts and model are presented in the Appendices). Section 4 describes the implementation of our model, in particular specifying the used observation fields (derived from multispectral satellite measurements), the assumed interactions (derived from acquisition and scene geometries) and the algorithm. Section 5 shows the obtained results, and Section 6 gathers our conclusions.

2. Study context and database AMMA/SPOT

2.1. AMMA database

The important inter-annual variability of the monsoon in West Africa is a phenomenon – with sometimes dramatic consequences – known and observed for several decades. However, this variability still raises a large number of questions both about the involved physical processes and about their social and economic consequences. The research program AMMA (African Monsoon Multidisciplinary Analysis) has hence two aims (Redelsperger et al., 2006). On the one hand, it tries to improve the comprehension of the monsoon in West Africa and its impact on the biosphere both at global and at local scales. On the other hand, it looks for the relationships between the climatic variability and the problems of health, water resources and food safety.

AMMA includes four interacting scales of observations. The larger one, the global scale, deals with the interactions between monsoon phenomenon and the remainder of the Earth. The monsoon process scale is the regional scale. The meso-scale deals with the interactions between atmosphere and watershed hydrology. At this scale, three study sites have been selected within West Africa, namely the Ouémé watershed in Benin, the Gourma one in Mali, and the Hapex square degree in Nigeria. Finally, over each of these sites, some 'super-sites' have been selected for studies and measurements at local scale studying the impacts of the climate on agriculture and antropic activities and the associated retroactions. At this scale, the characterization and the monitoring of surface state from remote sensing data require high spatial resolution sensors (pixel size of about few tens of meters). This requirement is fulfilled by SPOT4/HRVIR images. The whole database includes 39 SPOT/HRVIR scenes, whose acquisition dates and places are given in Table 1.

Finally, for algorithm performance evaluation, some cloud masks have been obtained by photointerpretation. In the lack of more objective data, these masks have been used as 'ground truth' to estimate the performance of the proposed automatic image processing method.

2.2. SPOT/HRVIR image features

The SPOT satellites, dedicated to the observation of the emerged surfaces, have quasi-polar, circular and heliosynchronous orbits at 832 km altitude. The fourth one (SPOT4) has two identical optical sensors HRVIR (High Resolution Visible and InfraRed on board), having a 60 km swath and acquiring panchromatic or multispectral images. In this last acquisition mode, measurements are performed in four bands (corresponding to wavelengths from green, to mid-infrared through red and near-infrared) with pixel size equal to 20×20 m^2.

As for any visible/infrared optical sensor, the acquired images may be affected by the presence of clouds. We propose a generic automatic cloud/shadow detection method. The proposed one is generic and would be applicable to any image provided that the basic assumptions (P1, P2, and P3) are valid. First, note that the separation of clouds (respectively shadows, respectively mist) from the remainder of the image is a non-trivial problem in most application cases. In particular, it is generally not possible to determine a decision threshold by simple analysis of the image histogram. Fig. 1 points out this difficulty. It compares, for each of the four spectral bands, the histograms of the pixels of soil and those of clouds in the case of a typical scene (extracted from the image acquired at 04/29/2006 over Benin). Whatever the spectral band, there is an important overlapping between soil and cloud histograms, inducing important rates of false alarms or misdetection regardless of the chosen threshold value. The only case where a threshold approach would be efficient is when the images only present completely opaque clouds. Besides, note that, even in this case, the threshold value can generally not be obtained from image histogram analysis because the cloud pixels are minor relative to the soil pixels.

3. Markov Random Field modelling

In this section, we recall the main concepts of the Markov Random Fields (MRF). We also introduce the notations used in the following sections. In the following section the general model is presented whereas its practical implementation described in Section 4.

MRFs are widely used in image processing (Abend et al., 1965; Geman and Geman, 1984) providing a solution to the causality problem. Nowadays, research is still active in this domain. Some work has focused on the development of efficient optimization techniques, in particular using graph cut methods (Boykov et al., 2001; Boykov and Kolmogorov, 2004; Kolmogorov and Zabih, 2004). Some other approaches aim at considering models more and more flexible, in particular relaxing the stationarity assumption of the image (Benboudjema and Pieczynski, 2005; Pieczynski and Benboudjema, 2006; Le Hégarat-Mascle et al., 2007), or models at higher level, in particular using MRF to model the relationships between image objects (Descombes, 2004).

3.1. Markov fields over graphs

Let G be a non-oriented graph. We assume that the edges of G define a neighbourhood system where V_s is the neighbourhood associated to node s, i.e. a set of nodes all having an edge toward s and checking $t \in V_s \Leftrightarrow s \in V_t$. The cliques c associated to V_s are defined as the union of some subsets of V_s and s such that a clique is a complete subgraph of G (constituted by 2×2 nodes considered to be neighbours; for example, Fig. 2 shows the possible cliques containing a pixel s, in 8-connexity over the pixel graph). Then, C denotes the set of cliques c over G.