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A graph-based approach to detect spatiotemporal dynamics in satellite image time series

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ABSTRACT

Enhancing the frequency of satellite acquisitions represents a key issue for Earth Observation community nowadays. Repeated observations are crucial for monitoring purposes, particularly when intra-annual process should be taken into account. Time series of images constitute a valuable source of information in these cases. The goal of this paper is to propose a new methodological framework to automatically detect and extract spatiotemporal information from satellite image time series (SITS). Existing methods dealing with such kind of data are usually classification-oriented and cannot provide information about evolutions and temporal behaviors. In this paper we propose a graph-based strategy that combines object-based image analysis (OBIA) with data mining techniques. Image objects computed at each individual timestamp are connected across the time series and generates a set of evolution graphs. Each evolution graph is associated to a particular area within the study site and stores information about its temporal evolution. Such information can be deeply explored at the evolution graph scale or used to compare the graphs and supply a general picture at the study site scale. We validated our framework on two study sites located in the South of France and involving different types of natural, semi-natural and agricultural areas. The results obtained from a Landsat SITS support the quality of the methodological approach and illustrate how the framework can be employed to extract and characterize spatiotemporal dynamics.

1. Introduction

Nowadays, satellite image time series (SITS) is a powerful source of information for monitoring purposes. Repeated satellite observations allow to follow the evolution (e.g. growing season, land-cover modifications) of a given area over the time in a systematic way. When repeatability and homogeneity of satellite observations are guaranteed it becomes possible to detect spatiotemporal evolutions and deduce their related dynamics (Bonn, 1996). However, the interpretation and the cross-comparison of several satellite images quickly become challenging.

Advanced methods used to process multitemporal optical imagery are related to trajectory analysis. In this context, high-temporal frequency SITS from coarse to moderate sensors, such as MODIS, are used to model temporal signatures and detect anomalies or trends (Lunetta et al., 2006; Verbesselt et al., 2010; Cai and Liu, 2015). Although powerful, these methods are hardly adaptable in finer spatial scales applications where the number of images available is lower and the temporal sampling is irregular. However, several local scale applications need high frequency of observations at intra-annual basis. Mapping and monitoring natural and agricultural areas with an enhanced revisit capacity allows monitoring phenology states, agricultural practices and seasonal processes. Recent reviews about conservation monitoring (Nagendra et al., 2013) and Natura 2000 habitat monitoring (Vanden Borre et al., 2011) pointed out remote sensing as a strong, but still underexploited, tool.

In the literature, methods used to process multitemporal optical imagery are commonly grouped under the change detection label. In a pioneer review article, Singh (1989) defined change detection as the process of identifying differences in the state of an object or

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phenomenon by observing it at different times. The author also categorized the main change detection techniques in ten different groups. A critical review about change detection methods in ecosystem monitoring was provided by Coppin et al. (2004). More recently, Hussain et al. (2013) expanded the change detection categories previously proposed by Singh (1989), including object-based change detection (OBCD) techniques. Regarding this last point, the works of Chen et al. (2012) and Blaschke (2005) provided a deep overview of the available OBCD methods.

Considering SITS of optical imagery, we can highlight two main limitations in the current literature. Firstly, most of the existing methods focus their efforts on bi-temporal change detection situations, i.e. the study of temporal evolutions taking place between two dates. Usually, these methods include post-classification comparison (Yuan et al., 2005), image differencing (Lu et al., 2005), composite analysis (Descle and Bogaert, 2006), linear transformation (Qin et al., 2013) and change vector analysis (Malila, 1980). Secondly, the majority of works explored mainly pixel-based strategies (Petitjean et al., 2012; Inglada et al., 2015) whereas object-based image analysis (OBIA) are still among open challenges in remote sensing analysis (Blaschke et al., 2014; Chen et al., 2012).

Petitjean et al. (2012) constructed vector images from SITS and used classical unsupervised classification (k-means) at pixel level. The originality of the approach consisted in the integration of spatial relationships between pixels. Each pixel was enriched by some contextual attributes coming from individual image segmentations performed at each timestamp. In this case, the temporal behavior (based on 15 FORMOSAT-2 images acquired in the same year) was used to assign a unique land cover label (mainly crops) to each pixel. These labels, derived from ground reference data, are static (e.g. corn) and do not describe dynamics (e.g. bare soil → growth of corn → harvest); therefore it is not possible to perform further analysis, or monitoring, related to the intra-annual evolutions. Inglada et al. (2015) evaluated the performance of state-of-the-art supervised classification methods for generating accurate crop type maps on 12 sites spread all over the world. The classification strategy giving the best results combined pixel-based temporal linear interpolation and feature extraction (radiometry derived features only). In this case, SITS were composed of a variable number of SPOT-4 and Landsat-8 images (from 9 to 41 images depending on the site) acquired in the same year. In general, important amounts of ground reference data (from several dozens to a few thousands of hectares) were necessary for training the classifier and achieving accurate results. Also here, the process chain generates a single outcome (i.e. a map) representing static land cover classes. This flat representation, alone, is not able to describe the evolutions and the temporal behaviors behind each class label.

Differently from previous approaches that mainly focus on the classification and/or detection of abrupt changes between consecutive images, this paper aims to describe a new methodology to explore SITS data detecting and describing spatiotemporal entities/phenomena existing in the study area. More in detail, given a time series of remote sensing images and an associated segmentation, our objectives are to: (i) detect the set of spatiotemporal entities/phenomena existing in the study area and (ii) supply a spatiotemporal description for each of them. To this end, we propose an hybrid methodology combining OBIA and data mining techniques. Our proposal firstly identifies a set of spatial entities covering as much as possible the whole study site and, subsequently, for each of those spatial entities, it builds an evolution graph to describe its temporal evolution.

We applied our approach on two study sites involving different types of natural, semi-natural and agricultural areas. Since the task we address is completely exploratory and different from most of the previous researches on SITS data (e.g. change detection, classification), to verify and assess the quality of our proposal we performed in-depth qualitative evaluations on the set of evolution graphs we extracted. More in detail, we showed how the evolutions graphs well summarize the temporal profiles of the extracted spatiotemporal phenomena and how they can be employed to synthesize the evolutions and temporal behaviors extracted from a SITS.

The rest of the paper is organized as follows: Section 2 describes all the methodological steps of the proposed approach. Section 3 presents the study case context, namely the time series data, the preprocessing steps and the verification strategies. Experimental results are presented and discussed in Section 4. Conclusions are drawn in Section 5.

2. Methodology

2.1. Object-based temporal evolutions

The type of phenomena we want to capture are spatiotemporal evolutions (and their related dynamics) describing how an entity (i.e. a lake, a saltmarsh area, a crop field, etc.) evolves along the time. To this purpose, within a given study site, the first goal of our approach is to automatically detect a set of spatiotemporal entities. Subsequently, a high-level description is constructed for each of those entities employing a graph-based representation. The general framework of our methodology is summarized in Fig. 1.

Given a SITS data and its associated segmentation, firstly we select a set of objects that represent the spatial entities we want to monitor during the time. We call such subset of objects Bounding Boxes (*BBs*). The set of *BBs* can contain objects coming from any timestamp. The term spatial entities is used in this paper to designate a part (any portion) of a given study site. Then, for each Bounding Box (*BB*), we create an evolution graph considering all the objects, in all the timestamps, that are covered by the *BB* area. Each vertex of a graph corresponds to an object. Two vertices are linked by an edge if they belong to two successive timestamps and the corresponding objects overlap each other. Creating the graph in such a way allows to link together objects that span over the same area through the time. The procedure is applied to each BB and the result consists in a set of evolution graphs summarizing the different spatiotemporal phenomena existing in the study site. The set of evolution graphs is successively exploited, with the object related information (e.g. spectral, geometrical, textural, etc.) in order to supply analysis at graph and study-site levels. The first level allows namely the analysis of the temporal trajectories (or profiles) of a particular spatiotemporal phenomenon while the second level supplies a more general picture summarizing the temporal dynamics detected over the entire study site.

2.2. Bounding box selection

The first step of our process consists in the selection of coherent *BBs* (i.e. spatial entities) to monitor along the different timestamps. This operation analyzes all the objects provided by the input segmentations (all the timestamps) and selects a subset of different spatial entities covering as much as possible the whole study site. To deal with this task we made some assumptions that are justified from the nature of the SITS data we manage.

The first assumption we made is related to the fact that each selected BB has, during the period considered by the SITS, a maximal extent (or footprint) from a spatial point of view. For instance, if we consider a temporary lake, in the time series we will have a timestamp in which it reaches its maximal spatial extent while for the other timestamps the same area may be