1. INTRODUCTION

Change detection is one of the most important applications of the automatic analysis of multitemporal remote sensing images. The availability of very high resolution (VHR) data (e.g., images acquired by Quickbird, Ikonos, SPOT-5 and WorldView satellites) results in a new set of possible applications, which require the generation of change-detection maps characterized by both a high geometrical precision and the capability of properly modeling the complex objects/areas present in the scene at different resolution levels. Classical change-detection techniques [1] result ineffective on VHR images, as they often assume spatial independence among pixels, which is not reasonable in VHR data, where the spatial autocorrelation cannot be approximated as a pulse function. In the literature, some unsupervised approaches have been presented, based on the comparison between features computed on homogeneous regions obtained according to segmentation procedures [2],[3]. Despite these context-sensitive methods are implicitly suitable to analyze VHR images, they model images (and thus changes) at a single scale (resolution) level, while VHR images include information at different scales. This information should be properly exploited to obtain reliable change detection maps. Some attempts to model the change/no-change information at different scales can be found in [4],[5]. Nonetheless, the method in [4] does not explicitly consider the spatio-contextual information, while the one in [5] models it by means of a fixed size neighboring system which is not always appropriate especially in border regions. A first tentative to jointly exploit the spatio-context and the multiresolution information for change detection is given in [6], where a multilevel extension of the change vector analysis is presented, which involves feature vectors that properly represent the multilevel and multitemporal context information of each investigated spatial position. This method results in a simple representation of the change information, but it does not explicitly model the correlation among different resolution levels.

In order to overcome the limitations of the above-mentioned techniques, in this paper we propose an adaptive multiscale random field for unsupervised change detection in VHR multitemporal images.

2. PROPOSED CHANGE DETECTION TECHNIQUE

Let us consider two VHR images acquired over the same geographical area at different times. The proposed technique derives in an automatic and unsupervised way the change detection map by: a) modeling the change information hierarchy according to an adaptive (parcel based) multiscale random field; b) estimating the label of each considered pixel according to a sequential estimation process that starts from the coarsest scale and reaches the finest one [7].

2.1 Multiscale adaptive random field model

In the first step a multiscale random field model composed of a series of adaptive random fields at different scales is generated. This kind of representation is achieved employing multitemporal and multilevel parcels. Multitemporal parcels represent the local adaptive neighborhood of pixels, and have the property to be homogeneous on both
considered temporal images. In order to characterize the spatio-temporal context of each pixel taking into account a context hierarchical multiscale representation, we adopt a two step procedure based on: i) independent hierarchical segmentation of multitemporal images from the pixel level to higher levels of representation of their spatial context; and ii) multitemporal fusion of the two segmentations obtained from step one [6]. The adopted procedure guarantees that a random field related to a specific pixel at a given level is completely included in the field of the same pixel at a coarser level.

The sequence of adaptive random fields from coarse to fine level represents a Markov chain. Therefore the conditional statistical distribution of the classes of change and no change at a given level can be written as a function of only the previous coarser scale.

2.2 Sequential MAP labeling

The labeling of each pixel in the considered dataset is faced by a sequential application of the MAP criterion that starts from the coarsest scale and proceed until the finest one. Assuming that the conditional statistical distributions of the classes at the coarsest level are known (or can be easily estimated from the data) and thanks to the properties of Markov chains, it is possible to sequentially estimate the conditional statistical distribution of the classes at finest level. Once the sequential estimation procedure terminates, the MAP criterion can be applied at the finest scale in order to assign the labels to the pixels (i.e., in order to compute the desired change detection map). It can be proven that, besides the knowledge of the conditional statistical distribution of the classes, the application of the MAP criterion requires the knowledge of the coarse to fine transition probabilities from a class to the other (i.e., the probabilities that a given pixel can change its label when moving from a coarser to a finer level). The estimation of such probabilities is achieved by applying the Expectation-Maximization algorithm, which is initialized according to either: i) prior information (if available); or ii) the assumption of equal values for all the transition probabilities.

For space constraints the analytical and complete formulation of the technique will be reported in the full paper.

3. EXPERIMENTAL RESULTS

In order to assess the effectiveness of the proposed technique, several experiments were carried out on VHR multispectral and multitemporal images acquired: i) by the Quickbird sensor on the Trentino area (Italy) in October 2005 and July 2006, and ii) by the SPOT-5 sensor on the Arcachon basin, located on the French Atlantic coast in August 2003 and June 2006 (see [8] for further details on this data set). Results obtained on these data confirmed the effectiveness of the proposed adaptive and multiscale technique, which significantly increased the change detection accuracy with respect to other methods reported in the literature (and used as benchmark in our experiments), and effectively modeled both homogenous areas and geometrical details in the final change-detection map. In particular, the proposed technique exhibited: i) high insensitivity to noise present in the images; ii) high capability to model the geometrical details of the scene; iii) high capability to detect changes associated with different scales; and iv) strongly lower computation complexity than traditional Markov Random Filed based approaches. For space constraints, greater details on the proposed technique and the experimental results will be reported in the full paper.

REFERENCES