Change Detection based on Adaptive Markov Random Fields

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Abstract

Usually changes in remote sensing images go along with the appearance or disappearance of some edges. In addition, pixels located along the edges are likely to weakly influenced by its neighborhood pixels, while pixels located far from the edges commonly have a tightly correlation among them. In this paper, we propose a novel change detection technique based on adaptive Markov Random Fields (MRFs) for high resolution satellite images with combined color and texture features. The technique is composed of two main steps: 1) the input images are marked with different region indexes by the combined color and edge features; 2) change maps are obtained under the MRF framework with alterable order of neighborhood and variable smooth weight coefficient controlled by the index map. The main contribution of this paper is that the spatial-contextual information included in the remote sensing imagery is correctly and adaptively exploited under an adaptive MRF framework. Experiments results obtained on a set of remote sensing imagery confirm the effectiveness of the proposed approach.

1. Introduction

Change detection is one of the most important applications of the remote sensing technology [1] [2]. With the advent of high resolution (HR) satellite imagery, not only the spectral feature but also other spatial information (color, texture, context) play their relevant roles. Most of the existing techniques described in literature model the spatial-contextual information included in the neighborhood of each pixel by using statistical texture models. Markov Random Fields (MRFs) [5] is a commonly used generative model to incorporate contextual information included in the neighborhood of each pixel [3, 4, 6]. In [3], a simple approach to the MRF modeling is used and an optimal change map is obtained by means of Maximum a Posteriori (MAP) decision criterion. This approach has been extended in [4] by using a fuzzy HMC (f-HMC) model which combines both statistical and fuzzy approaches to address the unsupervised change detection task in the SAR context. A multi-resolution model for Gaussian Markov Random Fields (GMRF) for application in texture segmentation is proposed in [6], where GMRF parameters were estimated from coarser to fine resolution. However, most of the existing methods do not make full use of color and texture information which are among the most expressive visual features.

In this paper, we present a novel change detection technique for high resolution remote sensing imagery under the adaptive MRF framework with combined color and texture features. The main contribution is that the proposed technique correctly and adaptively exploits the spatial-contextual information included in the remote sensing imagery under the adaptive MRF framework. The paper is organized as follows: Section II describes the proposed change detection technique. The data sets used in the experiments and the performance of the method are described in Section III. Conclusions are drawn in Section IV.

2. Change Detection with Adaptive MRFs

Edge is a prominent feature of an image. An edge is a boundary or contour in an image at which a significant change occurs in some physical aspect of the image. Usually, when there is a change between the remote sensing images, there will be some changes of edges. Therefore, the changes of edges can be seen as an important clue to the change detection. Additionally, pixels located along edges in most case have different labels and are weakly influenced by its neighborhood pixels, while pixels located far from the edges are more likely to belong to the same label with a tightly correlation among them.

2.1. The Combined Color and Edge Features

The Edge Histogram Descriptor (EHD) is one of the recommended descriptors for the MPEG-7 standard representation [7]. An edge histogram in the image space represents the frequency and the directionality of the brightness changes in the image. The edge histogram difference in some degree characterizes the changes between the two images. In this paper, for each image block, we compute vertical, horizontal, 45-degree diagonal, 135-degree diagonal and non-directional five edge type strengths. After the edge histogram feature extracted on each original input image, a map of edge histogram difference *EH* (showing in Fig. 1(a)) with three levels, *no-change (N)*, and *uncertain-change (UC)*, *change (C)*, is obtained by comparing the edge histograms EH_1 with EH_2. Here, we choose the Earth Mover's Distance (EMD) [8] as the dissimilarity measure.

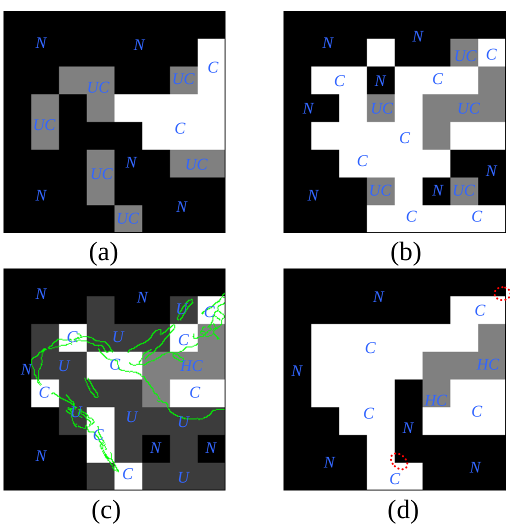

Figure 1. Illustrations of the color and edge features. (a) Edge histogram difference map *EH*. (b) Dominant color difference map *DC*. (c) Combination of the rough edge map and the index map with uncertain type. (d) Final certain type index map.

In order to provide a compact description of the color changes of the input images, a set of dominant colors are analyzed to capture the variant properties between the images. The MPEG-7 Dominant Color Descriptor (DCD) [7] provides an effective, compact, and intuitive representation of salient colors in an image region. This descriptor consists of the dominant colors and their percentages in the region. The descriptor is defined by

$$F = \{\{c_i, p_i, v_i\}, s\}, \quad (i = 1, 2, ..., N) \tag{1}$$

Where c_i, is the *ith* dominant color, and p_i, is its percentage value, v_i, is the *ith* color variance. For DCD feature extraction, we use the approach depicted in [7]. A DCD difference map *DC* is computed and it is indexed with three levels, too. The map *DC* is illustrated in Fig. 1(b).

Considering the color feature and texture feature having their own advantages and disadvantages, it is wise to integrate the EHD and DCD together. As mentioned above, both edge feature map *EH* and color feature map *DC* have three different labels. Theoretically there will be nine different combinations which is unavoidably a heavy computational burden. To address this problem, we adopt a new measure showing in *Table 1*, where *N* is no-change, and *C* means the changes located along the edges, *HC* is the changes located far from edges, *U* is the uncertain type. The uncertain type *U* means that this region is difficult to be clearly marked with changed or unchanged label only by maps *EH* and *DC*. It needs to be analyzed further by incorporating new feature.

Table 1. The integration measure of the EHD and DCD. (N: no-change. C: changes located along the edges. HC: changes located far from edges. U: uncertain region.)

EHD \ DCD	*N*	*UC*	*C*
N	N	U	U
UC	U	C	HC
C	U	C	C

To give a clear answer to which type the region *U* belong to, we draw support from a rough (not exact) edge difference map. The edge difference map *E* is produced by a simple subtraction of the two input images' edge maps. It is known that exact edge extraction is a difficult problem. Therefore, it is convenient and feasible to make use of the rough edge for a clear definition of the region *U*, illustrated in Fig.1(c) (the rough edges marked in green). The decision rules are given as follows: For type *U*, if there is not any edge in this region, then this region is defined as unchanged region and labeled with *N*, or else it will be labeled with *C*. Fig. 2 illustrates how to combining the color feature with the texture features.

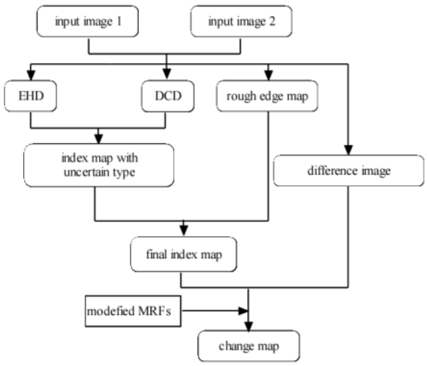

Figure **2**. Flowchart for the combination of color and texture features.

2.2. Change Detection based on Adaptive Markov Random Fields

MRF has long been recognized as an accurate model to represent the local statistical dependence of image. It provides a convenient and consistent way for modeling the spatial-contextual information included in the neighborhood of each pixel. The change detection problem under the MRF framework can be seen as a task of energy minimization. The energy function is given by:

$$E(X_R) = E_{data}(Y_{mn}, X_{mn}) + \lambda E_{sm}(Y_{mn}) \qquad (2)$$

Where $E_{data}(Y_{mn}, X_{mn})$ is the individual unary energy term, and $E_{sm}(Y_{mn})$ describes the inter-pixels class dependence. λ is the smooth weight. $E_{sm}(Y_{mn})$ is expressed in the follow relationship:

$$E_{sm}(Y_{mn}) = \sum_{\{(g,h),(m,n)\}\in Y} \delta_k(Y(m,n), Y(g,h)) \qquad (3)$$

Where $\{(g, h), (m, n)\} \in N$ represents the clique types in the neighborhood. $\delta_k(\bullet)$ is an indicator function. Therefore, the change detection problem can thus be solved by finding the least energy configuration of the MRF.

Usually, pixels located along the edges are more likely to have different labels and they are less influenced by its neighborhood pixels. Contrarily, pixels located far from the edges commonly belong to the same cluster and have a tightly correlation among them. To model the spatial-contextual information included in the neighborhood of each pixel more reasonably, we adopt a adaptive MRFs with the alterable order of neighborhood N and variable smooth weight λ . For pixels located in the region marked with index C, we adopt a small λ and the first-order neighborhood N_1; for pixels in the region marked with index HC, a large λ and a second-order neighborhood N_2 are chose; and pixels in region marked with index N are given the label unchanged directly without further detection. In this way, the adaptive MRF presents a more accurate model to represent the local statistical dependence of image. A final change map is obtained by minimization of energy function (2) using the ICM algorithm.

3. Experiments

In order to testify the validity of our approach, we carry out an experiment on a couple of Ikonos 2m resolution images, showing in Fig. 3. The images were acquired on January 10, 2003 and December 29, 2004 before and after the tsunami, over Aceh, Sumatra, Indonesia. After co-registration, each image had the size of 256×256 pixels.

(a) (b)

Figure 3. Indonesia data set. (a) Ikonos image acquired on January 10, 2003. (b) Ikonos image December 29, 2004.

To make a quantitative evaluation of the effectiveness of the proposed approach, we compare the change map obtained by our proposed technique with the one produced by general MRF approach. The reference map was obtained by Manual Trial-and-Error thresholding Procedure (MTEP), showing in Fig. 4(e). Fig. 4(a) illustrates the change map was produced by our proposed technique. The accuracy of the results are evaluated in terms of: 1) error rate (PE); 2) false alarm rate (PF); 3) missed alarm rate (PM). Table 2 gives a quantitative comparison based of the error typology.

Table 2. Comparison between the proposed approach and the general MRF approach.

Techniques	Missed alarms	False alarms	Overall error
Proposed approach	531	16	547
General MRF	450	265	715

The results obtained in our experiment confirm the validity of the presented change detection technique. Since pixels located close to the edges and ones located away from the edges have different correlations among the pixels in its neighborhood. Our proposed approach which makes full use of the edges information can not only retain the edge details capably but also keep the homogeneous areas smoothly. However, there are some obvious missed alarms (marked with red circles in Fig. 4(a)). The reasons are that both the changes of edges and colors are so blur (marked with red circles in Fig. 3) that those regions are mistaken as unchanged regions in the final index map (red circles in Fig. 1(d)). It can be seen clearly that the change map obtained by general MRF approach leaves many small holes among the unchanged areas (blue circles in Fig. 4(b)) one reason of which is that it use a fixed order of neighborhood N and a constant smooth weight λ.

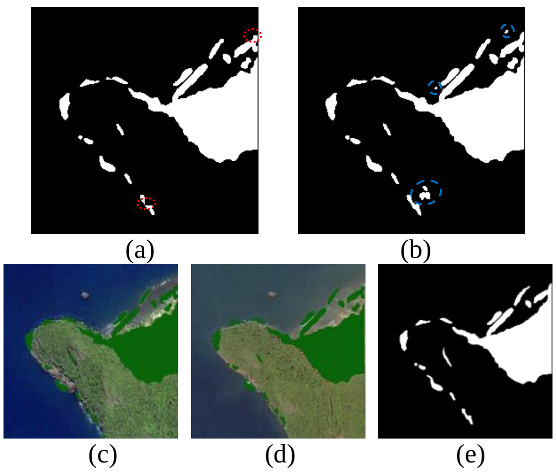

Figure 4. Change maps. (a) Change map obtained by our proposed technique. (b) Change map obtained by general MRF approach. (c), (d) **Mosaic images. (e) Reference map of the change area by using MTEP technique.**

4. Conclusions

In this paper, we present a novel change detection technique for high resolution remote sensing imagery under the adaptive MRF framework with combined color and texture features. Considering the phenomena that: 1) when there is a change between the images, there will go along with the changes of edges; 2) pixels located close to edges usually have different labels and are weakly influenced by its neighborhood pixels, while pixels located far from the edges are more likely to belong to the same label and have a tightly correlation among them, we propose a novel change detection approach under MRF framework with the alterable order of neighborhood and variable smooth weight coefficient. The choices of order of neighborhood and smooth weight coefficient are controlled by an index map which is formed by the combined color and edge features. The experiment results confirm that it is quite effective to use the combined color and edge features as the important clue to the changes between the images. The change map produced by the adaptive MRF can not only preserve edge details capably but also ensure the homogeneous areas smoothly. The main contribution of this paper is that the proposed technique exploits the spatial-contextual information included in the remote sensing imagery more adaptively. The main drawback is that edge extraction in some degree is a difficult problem, which may have some influence on the final change results.

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