Change Detection based on Conditional Random Field Models

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Abstract: - This paper addresses the problem of optical remote sensing images change detection based on conditional random field (CRF) models. CRF, a framework for building probabilistic models, offer several advantages over hidden Markov models for change detection. In this paper, we use the CRF to model the observed images and focus on analyzing the change detection by classifying the pixels of difference image to two different tpyes. Experimental results confirm the effectiveness of the proposed approach.

Key-Words: - Change detection; conditional random fields (CRFs); classification; remote sensing; optical images; Feature function.

1. Introduction

Change detection aims at discerning areas of change on digital images between two or more dates. This ability provides a fundamental image analysis tool in many diverse applications: 1) land cover monitoring, which principally consists in detecting the seasonal vegetation changes; 2)land use monitoring, which is the characterization of changes mostly due to human activities, like deforestation or urban development; and 3) damage mapping, which is the localization of changes caused by natural disasters like earthquake, floods, or forest fire, and which are usually supposed to be fast changes. Usually, Change detection aims at discerning areas of change on two registered remote sensing images acquired in the same geographical area at two different times. Two main approaches, supervised and unsupervised, are used to detect the change. The former is based on supervised classification methods, which require the availability of a ground truth in order to derive a suitable training set for the learning process of the classifiers. The latter performs change detection without any additional information besides the raw images considered. In this work, we are mainly concerned with the supervised classification methods, in which conditional random field models are used to build the probabilistic model for classifying the pixels of difference image to two different types.

Statistical characteristics information contained in images is quite useful for change detection. Most of the existing techniques described in literature model the spatial-contextual information included in the neighborhood of each pixel by using statistical models, which can be broadly characterized as either generative or discriminative. Markov Random Fields (MRFs) is a commonly used generative model to incorporate contextual information [1, 2]. MRFs are typically formulated in a probabilistic generative framework modeling the joint probability of the observed image and its corresponding change map. In this framework, the observed data is assumed to be conditional independent. However, this assumption is too restrictive for a large number of applications. This has led to research on discriminative models in literature of sequence labeling such as Conditional Random Fields (CRFs) [3]. Unlike MRFs, CRFs model the posterior directly, which leads CRFs would have better predictive performance in modeling the contextual information contained in observed images. CRFs have been generalized to many ways such as image segmentation [4], image classification [5], and object recognition [6].

In this paper, we present a novel approach to realize the change detection in optical images based on conditional random fields (CRFs). The main contribution of this work is that we integrate three feature functions under the conditional random field framework and a change detection approach is proposed based on conditional random field models. The paper is organized as follows: Section II describes the change detection algorithms based on conditional random field models. The datasets used are presented in Section III, which also contains a description of the experiment results obtained on a bidate set of optical images. Finally, conclusions and perspectives are drawn in Section IV.

2. Method

Let us consider two georeferenced and coregistered optical images $X_1=\{x_s|\ s \in S\}$and $X_2=\{X_s|\ s \in S\}$ acquired over the same geographical area but at two different time t_1 and t_2 respectively, where S is a set of sites contained within an image, and x_s is corresponding to the RGB values. Our aim is to generate a change detection map that represents changes that occurred on the ground between the acquisition dates. The change detection problem can be viewed as binary classification problem where each pixel is mapped into the set Y={y_s| s∈S} of possible labels.

2.1 Conditional Random Field Models

The definition of conditional random field (CRF) is given by Lafferty et al. in [7]. For two random fields X and Y over the remote sensing scene, (X, Y) is a conditional random field if, when conditioned on Y, the random field X obey the Markov property: P(Y_i|X, Y_j, i≠j)=P(Y_j|X,Y_j, j∈N_i), where Ni denotes the neighboring sites of point i. Thus, a CRF is a random field globally conditioned on the observation X. A conditional random field can be viewed as an undirected graphical model globally conditioned on X.

Given the observed image x, the solution is to find a configuration ý={$ý_1$, $ý_2$,…} by computing the maximum of a posterior p(y|x). A conditional distribution can be written as:

$$p(y \mid x,\lambda)=\frac{1}{Z(\Theta,x)}\exp(\sum_j \lambda_j F_j(y,x)) \quad (1)$$

Where Z(Θ, x) is the normalizing constant, and Θ={θ_s,θ_c,θ_t} is the model parameters. In this paper, we define the log conditional probability of the output y given the difference image x as:

$$\log P(y \mid x,\Theta)=\sum_{(i,j)\in\varepsilon}\sum_{k=1}^{K} f_k(y_i,y_j,x,i,j;\Theta)-\log Z(\Theta,x) \quad (2)$$

Where j is the neighbor site of i, and {f_k|1 ≤ k ≤ K} is a set of feature functions. In this paper, three feature functions are defined to model different cues and thus K is equal to 3.

2.2 CRF vs MRF

Compared with MRFs, CRFs typically have the following advantages[8]: 1) The main difference between CRFs and MRFs is that CRFs model a conditional distribution p(y|x) directly and does not include a model of p(x), which is not needed for classification anyway. This led CRFs would have better predictive performance; 2) CRFs make independence assumptions among y, but not among x; 3) All the parameters in CRFs are estimated simultaneously at the training stage and therefore, CRFs are typically very fast at inference stage; 4) The flexibility of the CRFs' formulation allows multi-components to be incorporated.

2.3 Feature Function

In this paper, three feature functions are defined to model different cues.

The first feature is a smoothness function that encourages neighboring sizes with the same label. Penalties are given when neighboring sites with different labels:

$$f_1(y_i,y_j,x,i,j;\Theta)=-\theta_s\delta_s(y_i,y_j) \quad (3)$$

Where θ_s is the weight of the function for tuning the influence of the spatial-contextual information on the change-detection process and $\delta_s(\bullet)$ is the indicator function, and is defined as:

$$\delta(y_i,y_j)=\begin{cases}1, if & y_i=y_j\\ 0, & otherwise\end{cases} \quad (4)$$

The second feature function is based on the color information. Color is a useful descriptor for change detection. Usually, scene change may go with the change of color. Unlike the RGB and CMYK color models, Lab color is designed to approximate human vision. Lab inherently provides some robustness to illumination changes. Therefore, we define the color feature function in Lab color space as:

$$f_2(y_i,y_j,x,i,j;\Theta)=\theta_c f_c(y_i,x_{ci}) \quad (5)$$

where θ_c is the weight of the function, x_{ci} (c∈Lab)is the Lab values of the pixel at site I, and $f_c(\bullet)$ is defined as:

$$f_c(y_i,x_{ci})=\frac{N_{y_i,x_{ci}}}{N_{x_{ci}}} \quad (6)$$

Where $N_{y_i,x_{ci}}$ is the number of pixels of class y_i with Lab value x_{ci} in the training data, and $N_{x_{ci}}$ is the total number of color x_{ci}.

The third feature function is defined by taking into the texture information of the images. As we known, texture is another powerful item of information for analyzing a scene. Haralick[9] proposed 14 statistical features extracted from gray level co-occurrence matrix to estimate image properties related to second-order statistics. Considering the computational complexity, only some of these features are widely used. In this paper, we use three most relevant features, namely energy, homogeneity and contrast, to describe the characteristics of the optical images. The function is defined as:

$$f_3(y_i,y_j,x,i,j;\Theta)=\theta_t f_t(y_i,x_{ti}) \quad (7)$$

Where θ_t is the weight of the function, x_{ti} is the statistical values of the images X_1 and X_2 in a proper window size, and $f_t(\bullet)$ is formed as:

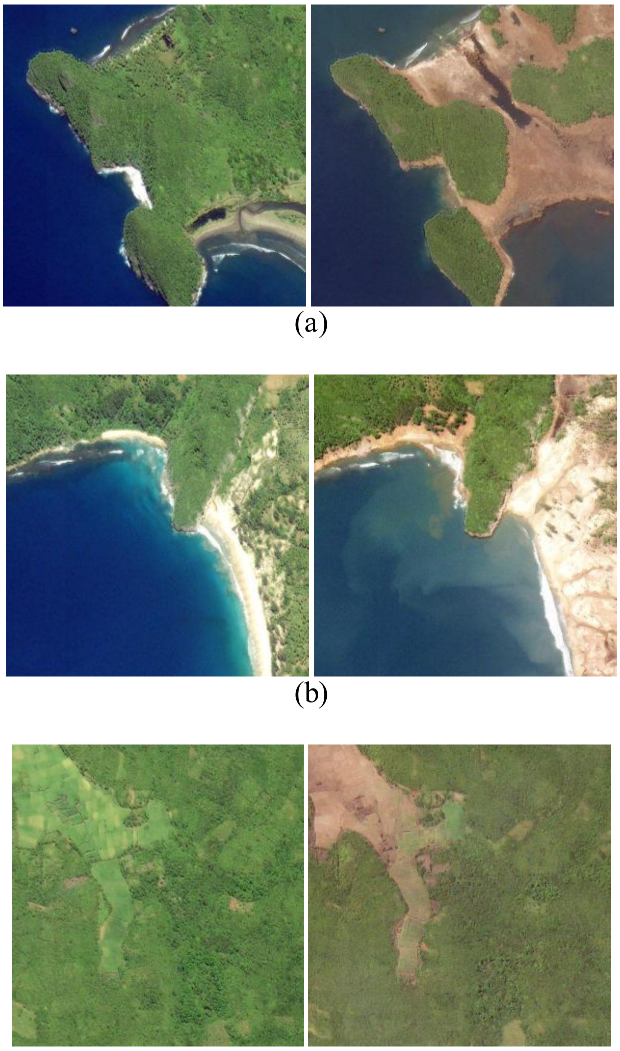
$$f_t(y_i, x_{ti}) = \frac{C_{X_i X_j}}{H_{X_i X_j} * E_{X_i X_j}} \tag{8}$$

$f_t(\bullet)$ indicates that when changes occurred between images, the energy and homogeneity of the two images will reduce and the contrast will increase.

3. EXPERIMENT

3.1 Dataset Description

The proposed algorithm was tested on two pairs of remote sensing images. The Ikonos 2m resolution images acquired before and after the tsunami on January 10, 2003 and December 29, 2004 respectively, over Aceh, Sumatra, Indonesia. After co-registration, each pair of images have the size of 3000×2880 pixels. We trained our system with four pairs of images sampled from the original images, with the size of 512×512 pixels each. Therefore, the training images account for 5.7 percents of the whole image in size. Some sample of the training images are show in Fig 1.



(a)

(b)

(c)

Fig 1. Some sample of the training images. The images on the left side are sampled from images acquired on January 10, 2003, and the ones on the right side are sampled from images acquired on December 29, 2004.

3.2 Parameter Estimation and Inference

After modeling of data, statistical model frameworks need to estimate parameters and infer labels.

3.2.1 Parameter Estimation

We train the conditional model discriminatively based on the Conditional Maximum Likelihood (CML) criterion, which maximizes the log conditional likelihood:

A gradient-based algorithm can be applied to maximize the conditional log likelihood. In this paper, we apply the contrastive divergence algorithm [10] to get the approximated optical parameters. The contrastive divergence algorithm is an approximate learning method that overcomes the difficulty of computing expectations under the model distribution. The contrastive divergence algorithm optimizes the parameters of a model by approximately maximizing conditional likelihood.

3.2.2 Inference

The problem for maximizing equation (1) can be transformed into an extremum problem. We need to infer the optimal label configuration Y given X. There are two main criteria for inferring labels from the posterior distribution [1]: maximum a posteriori (MAP)and maximum posterior marginals (MPM). Exact MAP is difficult to compute due to the high dimensionality and discrete domain of L. The MPM criterion, which minimizes the expected number of the mislabeled sites by taking the modes of posterior marginals usually produces a better solution. In this paper, we adopt MPM to yield the approximate optimal label configuration.

3.3 Experiment results

Fig. 2 and Fig. 3 show some representative results. In figure 2, we give some inferred results of the input training images. As expected, the inferred results of the training images are almost same as the ground-truth labels, which is also verified in other field where CRFs used. It can be seen in figure 2(b) that: 1) When the changes of the input images' color are not distinct, those changes may be neglected; 2) The smoothness function may result in the small changes missed; 3) In another way, the texture information of the images is well preserved by the smoothness function and the third feature function, the texture of the input images can be detected exactly.

(a)

(b)

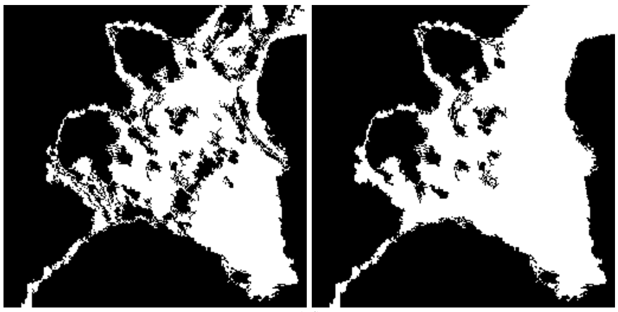
Fig. 2. The inferred results of the training images. (a) ground-truth labels; (b) inferred results;

We have made experiments on the whole original images, but with the limitation of the pages just some representative test results are given in figure 3. The inferred results of test images are satisfied. The possible reasons are that: 1) The training images and the tested images are all taken from the same original images, which enables the high similarity of them; 2) The high-resolution of the input images guarantee abundant texture information for training and inferring; 3) The changes between those high-resolution optical images caused by the tsunami are obvious and can be easily detected.

(a)

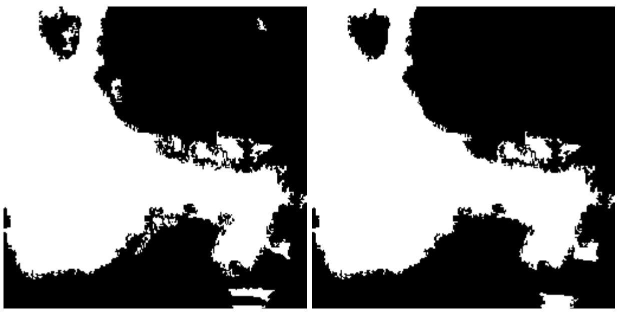
(b)

(c)



(d)

(e)



(f)

Fig. 3. Some representative results of the test images. (a), (c), (e) are the input images; (b), (d), (f) are the ground-truth labels and the inferred results.

4 Conclusion

In this paper, we present a novel optical remote sensing images change detection approach under the framework of the conditional random fields. The proposed approach uses the CRF to model the observed images and classifies the pixels of difference image to two different tpyes. Experimental results confirmed the effectiveness of the proposed approach. It shows that the introduced simple generic features, combined with the statistical model, have a good performance for change deection of the optical images.

The main drawbacks of this approach are those: 1) As this approach is based on CRFs, which need a large number of samples, it's not feasible for a pair of small-size iamges; 2) It's time-consuming for training features collecting. Future research may be related to more effective feature functions selection. For example, the color feature only is not robust for changes caused by illumination change.

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