Unsupervised change detection in high spatial resolution remote sensing images based on a conditional random field model

Guo Cao*, Xuesong Li and Licun Zhou

School of Computer Science and Technology, Nanjing University of Science and Technology, 210094, Nanjing, China
*Corresponding author, e-mail address: caoguo@njust.edu.cn

Abstract
In this paper, we propose a novel technique for unsupervised change detection in high spatial remote sensing images based on a conditional random field (CRF) model. The change-detection problem is formulated as a labeling issue to discriminate the changed class from the unchanged class in the difference image. CRF which employs the spatial property on both pixel’s spectral data and labels have been widely used in many remote sensing applications. However, as there are a large number of model parameters to train, the CRF-based change-detection approach is time consuming and difficult to implement. The proposed method artfully uses memberships of Fuzzy C-means as unary potentials and defines pairwise potentials using a scaled squared Euclidean distance between neighboring pixels. This not only avoids training parameters but also helps improving the accuracy and the degree of automation. The experimental results obtained from three different remote sensing images demonstrate the accuracy and efficiency of our proposed method.

Keywords: Change detection, conditional random field (CRF), Fuzzy C-means (FCM), remote sensing image.

Introduction
Change detection (CD) involves the analysis of two registered remote sensing images acquired in the same geographical area at two different times. It has been widely used in many remote sensing applications like urban development studies [Carlo et al., 2015], natural disaster damage assessments [Baiocchi et al., 2014; Bovolo and Bruzzone, 2007; Yang and Chen, 2010], environment monitoring [Smiraglia et al., 2014; Zewdie and Csaplovics, 2015]. Traditional change-detection methods can be classified into two categories: supervised approaches and unsupervised approaches. The supervised methods [Fichera et al., 2012] need some labeled samples for the training of a sequential classifier, while the unsupervised methods discriminate the changed class from the unchanged class without any prior information about the scene. Lacking of the ground truth in real applications makes the unsupervised approaches much more popular than the supervised
ones but less accurate. Generally, there are two pivotal steps in the process of unsupervised change detection [Bruzzone and Prieto, 2002]. One is to generate a difference image; the other is to use effective classification methods for analyzing the difference image and identifying the pixels or objects as changed or not. Both steps can affect the final results. For the first step, a difference image can be generated in three levels (pixel, texture and object levels) by applying the subtraction operator or the ratio operator to the spectral value of the two co-registered images. The subtraction operator is widely used in optical remote sensing images while the ratio operator is more acceptable to SAR images [Hou et al., 2014]. In order to suppress noise, the discrete wavelet transform [Celik and Ma, 2011] is exploited to obtain a multi-resolution representation of the difference image. Texture features [Gong et al., 2014] and object-level change features are also considered to generate the difference image [Huo et al., 2010].

For the second step, its aim is to detect changes from the obtained difference image. Most of classification methods can be applied to this task based on the so called difference image. Li et al. [2014] reviewed major remote sensing image classification techniques. In [Bruzzone and Prieto, 2000], two automatic techniques based on Bayes theory for the analysis of the difference image are proposed. Celik [2010] presented a change-detection method by conducting probabilistic Bayesian inference with Expectation Maximization (EM) algorithm based parameter estimation to threshold DT-CWT data. Celik [2009] detected the changes using principal component analysis and K-means clustering method. Level set based methods [Bazi et al., 2010; Celik, 2011] have been introduced into change-detection applications recently. Active contours evolve on the difference image using a multi-resolution approach. Wang et al. [2015] proposed an object-based change-detection approach in very high resolution satellite images using the cross-sharpening of multi-temporal data. In [Bruzzone and Prieto, 2000; Chen and Cao, 2013; Hao et al., 2013; Hao et al., 2014], the observed images are modeled as Markov Random Fields (MRFs) for change detection. MRFs are generally used in a probabilistic generative framework that models the joint probability of the observed image and its corresponding change map. However, the contextual information term in the model does not take the observed data into account. In addition, in this framework, the observed data is assumed to be conditional independent. This assumption is too restrictive for a large number of applications.

In recent years, different CRF models have been proposed in many applications including image labeling [Yu et al., 2012], classification [Hoberg et al., 2015], denoising [Zhong and Wang, 2014]. CRF models have become popular owing to their ability to directly predict the segmentation/labeling given the observed image and the ease with which arbitrary function of the observed features can be incorporated into the training process. In addition, CRF has the intrinsic ability to incorporate the contextual information in both the labels and the observed data. To improve the change detection accuracy, an automatic change-detection method is proposed by analyzing the difference image based on our modified traditional CRF model. In the model, unary potential is defined by using Fuzzy C-mean clustering results on feature vectors generated by applying principal component analysis (PCA). Pairwise potential is computed using a scaled squared Euclidean distance between the neighboring pixels. A chief advantage of our approach is to be able to obtain correct results without training model parameters. By contrast, most image differencing CD methods, like Volpi’s
[Volpi et al., 2012] method, often have noisy outputs like isolated changed pixels, holes in the connected changed components or jagged boundaries as a result of not considering the spatial relations among image pixels. With our modified CRF model, the boundaries of the changed class become smooth and the results are robust against noise. The paper is organized as follows: in Section “Conditional random field”, a brief introduction of the CRF model is given, Section “Proposed change-detection approach” presents the proposed change-detection method, the experimental results are discussed in Section “Experimental results”, and finally, Section “Conclusion” draws the conclusion.

Conditional random field
CRF was proposed by Lafferty et al. [2001] in the context of segmentation and labeling of 1-D text sequences. Then, Kumar et al. [2003] extended the 1-D CRFs by proposing the use of local discriminative models to capture the class associations at individual sites as well as the interactions on the neighboring sites on 2-D regular or irregular lattices. In recent years, CRFs are widely used in image classification and labeling tasks [Zhang and Jia, 2012; Benson et al., 2014; Zhong et al., 2014].

Let us denote the set of labels as \( Y = \{ y_i, i \in S \} \) with a label defined for every pixel in the set of pixels \( S \) in a given image \( X = \{ x_i, i \in S \} \). Each label is taken from a label space \( L \) such that \( y_i \in L = \{ l_1, l_2, \ldots, l_k \} \). CRF is a discriminative model, which can directly model the posterior probability of the labels given by the observations. If we denote the exact CRF distribution as \( P(Y \mid X) \) then the Gibbs energy for the CRF model assuming only up to pairwise clique potentials to be non-zero is given as

\[
E(Y \mid X) = \sum_i \phi_i(y_i) + \sum_{j \neq i, j \in S} \phi_{ij}(y_i, y_j) \quad [1]
\]

where we have \( p(Y \mid X) = \frac{1}{Z(X)} \exp(-E(Y \mid X)) \), \( Z \) is the normalizing constant known as the partition function. \( \phi_i(y_i) \) and \( \phi_{ij}(y_i, y_j) \) are the unary (association) and pairwise (interaction) potentials respectively.

Proposed change-detection approach
In this paper, we propose to solve the change-detection problem by means of a CRF labeling method. In particular, we consider implementing an unsupervised CRF model for the difference image and the observed multi-temporal images. The CRF model and energy functions are modified to seek to split the difference image into two mutually exclusive regions associated with changed and unchanged classes respectively. The procedure of our method is described in Figure 1.

\( X^1 \) and \( X^2 \) denote two co-registered multi-spectral remote sensing images acquired over the same geographical area at two different times. \( X_d \) is the difference image generated from \( X^1 \) and \( X^2 \) by applying PCA technique [Celik, 2009]. \( Y = \{ y_i, i \in S \} \) denotes the change map and \( y_i \in \{0,1\} \), in which 0 means changed and 1 denotes unchanged. Then, the
distribution model for change detection is defined as

\[ p(Y \mid X^1, X^2, X_d) = \frac{1}{Z(X^1, X^2, X_d)} \exp(-E(Y \mid X^1, X^2, X_d)) \]  \[ \text{[2]} \]

where \( Z(X^1, X^2, X_d) \) and \( E(Y \mid X^1, X^2, X_d) \) are the normalizing constant and CRF energy function respectively. The Gibbs energy for the CRF model assuming only up to pairwise clique potentials to be non-zero is given as

\[ E(Y \mid X^1, X^2, X_d) = \sum_i \phi_i(y_i) + \lambda \sum_{i \neq j} \phi_{ij}(y_i, y_j) \]  \[ \text{[3]} \]

as stated previously, \( \phi_i(y_i) \) and \( \phi_{ij}(y_i, y_j) \) are the unary and pairwise potentials respectively. \( \lambda \) is a weighting parameter to tune the unary and pairwise terms.

![Figure 1 - Flowchart of our CRF based change detection method.](image)

**Unary potential**

In the change-detection task, it is difficult to describe changes due to different remote sensors and image resolutions using fixed classifying parameters. Clustering algorithm can adaptively generate two clusters over the difference image. Thus, we adopt FCM algorithm to define the unary potential using only the difference image.

The objective function of FCM to be minimized is

\[ J_m = \sum_{i=1}^{L} \sum_{k=1}^{K} u_{ki}^m (x_i^d - v_k)^2 \]  \[ \text{[4]} \]

where \( L = 2 \) and \( m \in (1, \infty) \) is the fuzzy coefficient. \( u_{ki} \in [0,1] \) is the pixel \( i \) belonging to cluster \( k \) and follows the constraint \( \sum_{k=1}^{L} u_{ki} = 1 \). We get the cluster mean and fuzzy membership after \( b \) iteration times:
The unary potential can then be represented as:

$$\phi_i(y_i, x_d; \theta_p) = -\sum_{i=1}^L \delta(y_i = l) \log(\mu_{li}^{(b)}) \quad [5]$$

where $\delta(\cdot)$ is Dirac function.

**Pairwise potential**

The output of the unary classifier for each pixel is produced independently from the outputs of the classifier for other pixels. The MAP labeling by unary classifier alone is generally noisy and inconsistent. The pairwise potential can be seen as a measure of how the label at neighboring pixels $i$ and $j$ should interact given the observed image $X^1$ and $X^2$. It introduces a penalty for nearby similar pixels that are assigned different labels and helps to remove noises. The traditional CRF model is not efficient as it needs to train a large number of parameters. We adopt a boundary constraint based on Euclidean distance proposed by Zhang and Jia [2012] to define the pairwise potential in order to avoid training procedures. The pairwise potential can then be written as:

$$\phi_y(y_i, y_j; x; \theta_p) = \begin{cases} 1, & y_i = y_j \\ 1 - \exp\left(-\frac{d(x_i^k, x_j^k)}{2\sigma^2_k} - \frac{d(x_i^l, x_j^l)}{2\sigma^2_l}\right), & y_i \neq y_j \end{cases}$$

where $d(x_i^k, x_j^k)$ represents the distance between spectral vectors $x_i^k$ and $x_j^k$, $\sigma_i^2$, which can be interpreted as the scaling factor, is the mean value of $d(x_i^k, x_j^k)$ in the image $x^k$, so $\sigma_k^2 = \frac{1}{4N} \sum_{i=1}^N \sum_{j \in \delta} d(x_i^k, x_j^l)$. If the site $i$ and $j$ have the similar spectral vectors both in $X^1$ and $X^2$, $1 - \exp\left(-\frac{d(x_i^k, x_j^k)}{2\sigma^2_k} - \frac{d(x_i^l, x_j^l)}{2\sigma^2_l}\right)$ is close to 0; otherwise, close to 1. After modification, $\phi_y(y_i, y_j; x; \theta_p)$ becomes a scalar and no parameters need to be trained. If the current pixel $x_i^k$ and the neighborhood pixel $x_j^l$ are similar ($k = 1, 2$), under $y_i \neq y_j$, $\phi_y(y_i, y_j; x; \theta_p)$ will be close to zero, which means the smoothness will be supported. Otherwise, $\phi_y(y_i, y_j; x; \theta_p)$ will be close to one and the smoothness will be penalized heavily if boundary appears or change occurs.
The conventional CRF model needs to train a large number of model parameters. In our CRF based change-detection approach, unary and pairwise potentials are redefined, which makes the implementation of CRF simple and efficient.

**Difference image**

As mentioned in Section “Introduction”, the difference image generally is produced by subtracting the images acquired at two times on a pixel basis. Changes are then identified by analyzing the difference image. Celik [2009] presented a powerful difference image construction method based on principal component analysis (PCA). The difference image is partitioned into $h \times h$ non-overlapping blocks. $S, S \leq h^2$, orthonormal eigenvectors are extracted through PCA of $h \times h$ non-overlapping block to create an eigenvector space. Each pixel in the difference image is represented with an $S$-dimensional feature vector which is the projection of $h \times h$ difference image data onto the generated eigenvector space. We refer the reader to [Celik, 2009] for further details. Although Celik’s method has increased the robustness against noise, we still face such limitations as noisy outputs when applying his algorithm in very high resolution images.

**Experimental results**

**Remotely sensed data**

Several multi-temporal remote sensing image data sets were applied in the proposed techniques. The first data set contains a high resolution ($6407 \times 5521$ pixels, 2.5m/pixel) set of SPOT5 multi-spectral images obtained over the region of Qingyuan district near Guangzhou in each December of 2006 and 2007 separately. During the two acquisition dates, some grassland became barren and some new buildings were constructed. The second data set is composed of two high resolution images of size $291 \times 263$ acquired over an urban region in July of 1999 and June of 2000. During that period, new residential buildings were constructed and part of grassland became barren. The third data set represents two images of size $560 \times 424$ acquired over the island of Elba in Italy by the Landsat-5 TM sensor in August and September of 1994, respectively. A fire occurred between the two acquisition dates.

**Results and discussion**

To assess the effectiveness of the proposed method, we compared our method with other pixel-based CD methods including multi-resolution level set change-detection approach MLS [Bazi et al., 2010], Thresholding method [Ostu, 1979], PCA-Kmeans [Celik, 2009], Kernel method [Volpi et al., 2012], MRF [Bruzzone and Prieto, 2002] and traditional CRF based algorithms. In MLS, the parameter settings are the same to [Bazi et al., 2010]. We set $h = 5$ and $S = 3$ for the PCA-Kmeans algorithm and our method. For all experiments, the loopy belief propagation for approximate inference is used to approximate the mostly possible configuration and $\lambda$ is set 10 by trial and error in our method. All experiments were conducted on an Intel E7300 processor clocked at 2.66GHz with 2G memory. Our algorithm was implemented using C++.

In the first experiment, image pair which contains a large study area obtained by SPOT5 sensor was analyzed and a small area with $750 \times 1000$ pixels was selected and presented in...
Figure 2a and b. It is worth noting that the OSTU, MLS approach and the Kernel method produce noisy outputs in VHR remote sensing images as shown in Figure 2c, d and e. The PCA-Kmeans (Fig. 2d) use neighborhood information to find the change map and perform better against noise in images with respect to the aforementioned two methods. The MRF-based approach applies $3\times3$ contextual information to make a final decision on each pixel. The result based on MRF method is similar to that of PCA-Kmeans algorithm. The traditional CRF-based approach and our method also utilize local contextual information based on the observed images. They perform a little better than PCA-Kmeans and MRF-based methods. It should be noted that our method is an unsupervised approach and need no training procedures compared with the traditional CRF based technique.

Figure 2 - Change maps for the SPOT5 multispectral remote sensing images. (a)(b) mountain region data set, Dec. 2006-Dec. 2007; (c) MLS algorithm; (d) threshholding algorithm; (e) Kernel method; (f) PCA-Kmeans method; (g) MRF algorithm; (h) traditional CRF method; (i) proposed approach.
In another experiment, image pairs, ground truth and detection results with the different methods are shown in Figure 3. The visual comparison between the different changed results confirms the capabilities of the proposed approach in providing change results very close to the ground truth. However, the results of our model have a little over-smoothing appearance as shown in Figure 3h. Some small changed structures are removed.

Figure 3 - Change detection results. (a)(b) Original images taken in 1999 and 2000; (c) ground truth map; (d) MLS algorithm; (e) thresholding method; (f) PCA-Kmeans algorithm; (g) CRF method; (i) proposed approach.

Figure 4 describes the results in the third experiment. The OSTU, MLS, PCA-Kmeans and our proposed method are unsupervised change-detection approaches which are free of priori assumptions in modeling the data distribution of the difference image. In addition, these methods artfully avoid selecting thresholds to discriminate changed class from unchanged class, which is often a crucial problem in many existing methods. Furthermore, though PCA-Kmeans, MRF, CRF and our proposed method all incorporate the spatial information into their own model, we can see from Figure 4i that our method generates less noisy regions than the other methods. The proposed approach is not only robust against noise but also yields smooth boundaries of changed regions.

The ground truth of the change-detection maps was manually created based on the input remote sensing images, which were used to evaluate the accuracy of the obtained change maps in terms of: 1) error rate (PE), 2) false alarm rate (PF) and 3) missed alarm rate (PM). The first error measure was often considered as an important global detection performance criterion. The results regarding the numerical evaluation were reported in Table 1. We can observe that for the OSTU and Kernel method, each evaluation metric gave poor results. For the first data set, there indeed exist many small changed regions. The proposed approach has high detection performance. The three experiments demonstrate that the precision of the proposed algorithm was much better than the other algorithms. There always exist many small isolated false changed pixels as shown in Figure 2, 3 and 4. In contrast, our modified CRF based method is able to eliminate these noisy pixels.
Figure 4 - Change maps for the Elba data set. (a),(b) Band 4 of the Elba data set, August-September 1994, Landsat-5 TM; (c) ground truth map; (d) MLS algorithm; (e) thresholding method; (f) PCA-Kmeans algorithm; (g) MRF; (h) traditional CRF based algorithm; (i) proposed approach.

Table 1 - Error rate in percentage (%) achieved by the different methods.

| Method       | Figure 2a,b | Figure 3a,b | Figure 4a,b |
|--------------|-------------|-------------|-------------|
|              | PE          | PF          | PM          | PE          | PF          | PM          | PE          | PF          | PM          |
| MLS          | 5.94        | 4.42        | 23.15       | 0.54        | 0.38        | 3.90        | 0.40        | 0.19        | 10.99       |
| OSTU         | 11.19       | 9.04        | 35.45       | 1.17        | 0.94        | 6.11        | 7.33        | 7.46        | 0.88        |
| Kernel       | 7.89        | 7.55        | 12.17       | 16.02       | 16.08       | 14.61       | 34.12       | 34.36       | 21.89       |
| PCA-Kmeans   | 5.17        | 3.81        | 20.51       | 0.62        | 0.44        | 4.37        | 0.33        | 0.30        | 2.04        |
| MRF          | 7.28        | 2.55        | 60.73       | 2.74        | 2.80        | 1.36        | 1.54        | 1.52        | 2.68        |
| Traditional CRF | 4.77    | 2.52        | 30.30       | 1.07        | 0.30        | 17.46       | 0.25        | 0.19        | 3.42        |
| Our method   | 3.98        | 2.13        | 21.95       | 0.62        | 0.20        | 9.51        | 0.15        | 0.11        | 2.05        |
In addition, Generalization accuracy is accessed in terms of overall accuracy (OA) and estimated Cohen’s Kappa statistic [Foody, 2004] on our experiments. The quantitative results are tabulated in Table 2. The proposed approach shows a relatively high $k$ value indicating that it is a stable approach. The average $k$ score increased by 0.19, 0.2, 0.05 and 0.03 compared with MRF, MLS, traditional CRF based method and PCA-Kmeans algorithms respectively. The above experiments demonstrate that the precision of the proposed algorithm was much better than the above mentioned algorithms. In addition, our method is also fast. Take Figure 2 as an example, the proposed method in this paper only iterates no more than 10 times and needs about 40 seconds to obtain the change map.

### Table 2 - Accuracies for the Data Sets.

| Method       | OSTU | Kernel | MLS  | PCA-Kmeans | MRF  | Traditional CRF | Proposed approach |
|--------------|------|--------|------|------------|------|----------------|------------------|
| OA (%)       | 98.82| 94.82  | 85.68| 94.85      | 91.32| 95.23          | 96.01            |
| Kappa        | 0.43 | 0.62   | 0.19 | 0.69       | 0.58 | 0.68           | 0.73             |
|              | 0.87 | 0.27   | 0.94 | 0.93       | 0.75 | 0.87           | 0.93             |
|              | 0.32 | 0.05   | 0.89 | 0.92       | 0.70 | 0.93           | 0.96             |

**Conclusion**

In this paper, a new algorithm integrating FCM clustering and boundary constraint into a CRF framework has been proposed for change detection in high spatial resolution remote sensing images. Unary potential is defined using memberships of Fuzzy C-means on feature vectors which generated by means of PCA projection. Pairwise potential is described with a scaled squared Euclidean distance between the neighboring pixels. We modify the model style and avoid the training procedure which is often time consuming in parameter estimation. In addition, since the proposed CRF model incorporates the spatial contextual information, our proposed algorithm has the ability to obtain smooth boundaries of changed regions and robust against noise without manual parameter adjustment. Real data experiments demonstrate the effectiveness of the proposed approach, compared with other state-of-the-art change-detection algorithms, and they confirm that our method has a competitive quantitative and qualitative performance for remote sensing image change-detection task. Moreover, compared with MRF based change-detection approaches, contextual information in both images and labels can be incorporated into CRF model. This makes CRF model a very promising technique for generating accurate change-detection results. However, CRF model with only unary potential and pairwise potential does have over-smoothing performance in change-detection task as displayed in our experiments. One possible extension of this work is to combine high order potentials and object-based analysis in the CRF model, which will be a direction of our future work.
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