

A Semisupervised Context-Sensitive Change Detection Technique via Gaussian Process

Keming Chen, Zhixin Zhou, Chunlei Huo, Xian Sun, and Kun Fu

Abstract—In this letter, we propose a semisupervised context-sensitive technique for change detection in high-resolution multi-temporal remote sensing images. This is achieved by analyzing the posterior probability of probabilistic Gaussian process (GP) classifier within a Markov random field (MRF) model. In particular, the method consists of two steps: 1) A semisupervised initialization exploits both labeled and unlabeled data based on a probabilistic GP classifier, and 2) an MRF regularization aims at refining the posterior probability by employing the spatial context information. In particular, both edge information and high-order potential are utilized in MRF energy function formulation. Experimental results obtained on real remote sensing multitemporal imagery data sets confirm the effectiveness of the proposed approach.

Index Terms—Change detection, Gaussian process (GP), high-resolution (HR) image, Markov random field (MRF).

I. INTRODUCTION

COMPARED with unsupervised and supervised approaches, semisupervised change detection approaches recently have attained great attention in remote sensing field. From an operational point of view, these approaches are based on a more realistic assumption that, beginning with a small amount of labeled examples, the learning algorithm can equip itself with enough knowledge by taking advantage of abundant unlabeled data. Recently, kernel-based methods, such as support vector machine (SVM) and Gaussian process (GP), have been applied popularly to semisupervised remote sensing image change detection [1]–[5]. In [1], the promising semisupervised approach and the powerful SVM classifier were combined and applied to multispectral remote sensing image change detection. In contrast to SVM classifiers, GP classifiers have not yet

received sufficient attention from the remote sensing community [6], although the GP classifier is a theoretically attractive statistical model permitting a fully Bayesian treatment. In [3], a semisupervised change detection method was proposed to take advantage of both labeled and unlabeled data based on recent development in GP classifiers named null category noise model (NCNM) [7]. Experimental results on multitemporal remote sensing images reported in [3] have shown that NCNM could compete seriously with the state-of-the-art transductive SVM (TSVM) classifier for change detection. In spite of satisfactory performance, the approach does not take into account the spatial contextual information contained between neighboring pixels in the decision process, which may result in isolated noise in the final change map and may decrease change detection precision. To overcome the limitations imposed by neglecting the inter-pixel class dependence, Markov random field (MRF) model is popular in modeling image spatial context among pixels in neighborhood. Bovolo and Bruzzone [4] and Tarabalka *et al.* [8] had investigated the integration of SVM technique within an MRF framework, and good performance was reported.

With the advent of high-resolution (HR) satellite images, many new characters for HR image change detection enter in the focus. On the one hand, statistical distributions of these images become more complex, and the common unary and pairwise clique potentials in MRF model are insufficient for modeling rich statistics of a complex scene. As a result, even the global minimum of the MRF energy function may not correspond to the desired results [9]. On the other hand, more features, such as edge information and complicated structure interactions, may play their relevant roles in improving the performance of HR imagery change detection. Guiding the detection process with some helpful information possibly is a promising way.

In this letter, we propose a semisupervised context-sensitive technique for HR remote sensing image change detection via GP initialization and MRF regularization (named S^2CS -GP). The first step which is a popular semisupervised kernel-based initialization allows abundant unlabeled samples to be fully exploited in the GP classifier training process. Instead of a binary change map, the GP classifier predicts a probability value for every sample indicating to which degree the pixel will be detected as the changed one. To overcome the shortcomings of the GP classifier, the second step aims to employ the spatial contextual information for refining the GP posterior probabilities. This is achieved by means of MRF regularization. In particular, both edge information and high-order potential are utilized in MRF energy function formulation. The structure of the proposed approach is shown in Fig. 1.

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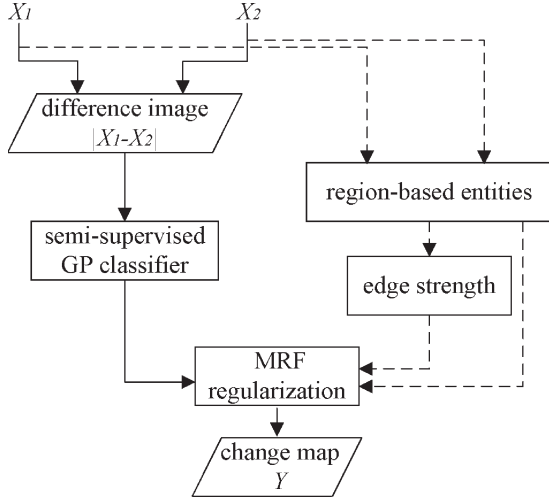


Fig. 1. Flowchart of the proposed S²CS-GP method.

The outline of this letter is as follows. In the next section, the S²CS-GP change detection scheme for HR images is presented. Experimental results are discussed in Section III, and conclusions are drawn in Section IV.

II. METHOD

Supposing two coregistered multitemporal images X_1 and X_2 , we aim to generate a binary change map Y indicating the changes and unchanges that occurred on the surface. Denote a training set $T = \{X_t, Y_t\}$ consisting of training data $X_t = [x_1 \ x_2 \ \dots \ x_l]^T$ accompanied with a label set $Y_t = [y_1 \ y_2 \ \dots \ y_l]^T$, where X_t is the difference image produced by $X_t = |X_1 - X_2|$ and l is the size of the training set. To each vector $x_i \in \mathbb{R}^d$ (d is the dimension of the feature set), a target $y_i \in \{+1, -1\}$ is associated, i.e., $f: x_i \rightarrow y_i$ ($i = 1, 2, \dots, l$). Given the training set T , the goal is to learn a mapping function $f^*: x_i^* \rightarrow y_i^*$ ($i = l+1, l+2, \dots, n$) that predicts the label of a testing sample $x_i^* \in X^*$ in the testing set $X^* = [x_{l+1}^* \ x_{l+2}^* \ \dots \ x_n^*]^T$, where $y_i^* \in Y^*$ is unknown.

A. Probabilistic GP Change Detection

Under the probability framework, $\{x_i^*, y_i^*\}$ is regarded to be subject to certain distribution $p(x_i^*, y_i^*)$ which is a joint distribution on $X^* \times Y^*$. When functional form of the posterior is known, a semisupervised learning problem is to determine $p(y_i^*|x_i^*, x_i, y_i)$ from labeled examples $\{(x_i, y_i)\}_{i=1}^l \in T$ with aid of unlabeled samples $x_i^* \in X^*$ ($i = l+1, l+2, \dots, n$). Thus, the probability of class membership is decomposed as

$$p(y_i^*|x_i^*, T) = \int p(y_i^*|f^*) p(f^*|x_i^*, T) df^* \quad (1)$$

where $p(y_i^*|f^*)$ is the noise model and $p(f^*|x_i^*, T)$ is the process model.

GP is a collection of random variables, any finite number of which has a joint Gaussian distribution [10]. It is fully specified by its mean function $m(x_i)$ and covariance function $k(x_i, x_j)$.

With the GP prior $p(f) = GP(m, k)$, the distribution of the process model corresponds to a test case

$$p(f^*|x_i^*, T) = \int p(f^*|X_t, x_i^*, f) p(f|T) df. \quad (2)$$

For the noise model, the NCM proposed in [7] involves a transductive learning process under a probabilistic framework in the presence of unlabeled data. Instead of traditional two categories, NCM maps a latent process variable f^* into three categories, specifically to the never used label “0” when f^* is around zero

$$p(y_i^*|f^*) = \begin{cases} H(-f^* + \frac{1}{2}), & y_i^* = -1 \\ H(f^* + \frac{1}{2}) - H(f^* - \frac{1}{2}), & y_i^* = 0 \\ H(f^* - \frac{1}{2}), & y_i^* = 1 \end{cases} \quad (3)$$

where $H(\cdot)$ is a Heaviside step function. Under the given assumptions in [7], unlabeled data can indeed influence the position of the decision boundary, which is similar to the margin in the context of TSVM classifiers. Model selection for GP involves choosing the kernel parameters and the noise variance.

Remarkably, instead of labeling the pixel in the change map as hard changed or unchanged class, each pixel is marked with a probability value indicating to which degree it will be detected as the changed one by the GP classifier.

B. MRF Regularization

As the GP classifier gives the predictions without considering the correlations between spatially adjacent pixels, it is wise to carry out a spatial regularization of the pixelwise change map. Conventional framework for such problems is the search for maximum *a posteriori* (MAP) configurations in an MRF model, which is formulated as minimizing an interaction energy function E

$$E = \sum_{x_i^* \in X^*} E_u(x_i^*, y_i^*) + \sum_{j \in N} E_p(y_i^*, y_j^*) \quad (4)$$

where N is a second-order spatial neighborhood system, E_u is the unary potential, and E_p represents the pairwise potential.

According to Bayes rule, the MAP labeling for pixel $x_i^* \in X^*$ ($i = l+1, l+2, \dots, n$) is defined as

$$P(Y^*|X^*) = \frac{P(X^*|Y^*)P(Y^*)}{P(X^*)}. \quad (5)$$

Under the MRF framework, supposing that the condition probability on each pixel is independent, the condition probability $P(X^*|Y^*)$ is decomposed into a product as

$$\begin{aligned} P(X^*|Y^*) &= \prod_{i=l+1}^n p(x_i^*|y_i^*) \\ &= \prod_{i=l+1}^n \frac{p(y_i^*|x_i^*) p(x_i^*)}{p(y_i^*)} \\ &= \prod_{i=l+1}^n \frac{p(y_i^*|x_i^*)}{p(y_i^*)} \prod_{i=l+1}^n p(x_i^*). \end{aligned} \quad (6)$$

Substituting the condition probability (6) into (5), we get

$$P(Y^*|X^*) = \prod_{i=l+1}^n \frac{p(y_i^*|x_i^*)}{p(y_i^*)} P(Y^*) \prod_{i=l+1}^n p(x_i^*)/P(X^*). \quad (7)$$

The prior probability $P(Y^*)$ models the intrapixel interactions which seek to keep the labels within neighborhood smoothness. Traditionally, multilevel logistic (MLL) model has been widely utilized under the assumption that pixels in a neighborhood present some coherence

$$p(Y^*) = \frac{1}{Z} \exp \left(- \sum_{y_j^* \in N} \beta \cdot \delta(y_i^*, y_j^*) \right) \quad (8)$$

where N represents the clique types in the neighborhood system of y_i^* . $\delta(\bullet)$ is an indicator function, and β is the smooth weight coefficient.

Picking some insights from the MLL model, we may find that the MRF spatial context model functions as a penalty for the existence of boundary between pixel pairs. However, a spatial context model with constant parameters penalizing equally for all boundary pixel pairs may be no longer suitable for a complex scene. As edge is a boundary or contour in an image, it is a prominent clue to indicate the significant change occurring between the multitemporal image pairs. Specially, changes in multitemporal remote sensing images usually go along with the appearance or disappearance of some edges. When changes take place, there will be some alterations of edges between the images. In addition, pixels located in different sides of an edge usually have different labels in the final change map and are weakly influenced by its neighboring pixels, while pixels located far from edges are more likely to be assigned the same labels and have tight correlations among them. Therefore, edge is a helpful feature to improve the performance of the spatial context model. Inspired by these observations, the proposed S²CS-GP intends to adopt an adaptive MRF spatial context model with the alterable parameters which applies a greater penalty to weaker edges for punishing the label inconsistency in homogeneous area.

Although the second-order MRF model is popular for modeling the spatial context, the pairwise potential has the limited expressive power for the high-level structural dependencies. Furthermore, the second-order MRF model generally makes the assumption that all pixels constituting a particular segment belong to the same class. However, this is not always the case. In HR remote sensing images, segments often contain pixels of multiple classes, particularly in complex urban environments. To improve the detection precision, high-order potentials derived from region-based entities are needed.

In this letter, an adaptive second-order potential is defined as a monotonically decreasing function about the edge strength e_{ij} for a boundary between labels y_i^* and y_j^* [9]. A high-order potential which takes the inconsistency of the segment s ($y_i^* \in s$) into account is defined in the form of

P^n Potts model [11]. Thus, the spatial energy function is defined as

$$p(Y^*) = \frac{1}{Z} \exp \left(- \sum_{y_j^* \in N} \beta' \cdot \delta(y_i^*, y_j^*) - \left(\sum_{y_j^* \in s} \delta(y_i^*, y_j^*) \right)^{\theta_s} \right) \quad (9)$$

where β' is the graduated increase edge penalty function proposed by Yu and Clausi [9]. θ_s is the penalty for label inconsistency. The segment s can be produced by oversegmentation methods, such as mean shift [12]. The second term in the right-hand side of (9) gives the label inconsistency cost that is a punishment for labeling the pixels in the segment with a label different from y_i^* .

According to (7), as $\prod_{i=l+1}^n p(x_i^*)/P(X^*)$ is a constant, the MRF energy function E in (5) is formed as follows:

$$E = \sum_{x_i^* \in X^*} [\log(p(y_i^*|x_i^*)) - \log(p(y_i^*))] + \sum_{y_j^* \in N} \beta' \cdot \delta(y_i^*, y_j^*) + \sum_{y_j^* \in s} \delta(y_i^*, y_j^*)^{\theta_s}. \quad (10)$$

$p(y_i^*|x_i^*)$ can be estimated by training, which can be achieved by using the initial predictions of the GP classifier. $p(y_i^*)$ can be calculated according to the prior about the proportion of changed and unchanged labels, which is achieved with the ratio of the labels in the last round of iteration.

III. EXPERIMENTS

To investigate the effectiveness of the proposed approach, four recently developed methods are tested and compared. The methods are as follows:

- 1) GP-based change detection (GPCD) method: a semisupervised change detection method based on NCNM reported in [3];
- 2) MRF-based change detection (MRFCDD) method: a context-sensitive method by analyzing the difference image under the MRF framework as reported in [13] but applied to HR multitemporal remote sensing images;
- 3) multilevel parcel-based change detection method (Bovolo's method): a parcel-based context-sensitive technique for change detection in very high geometrical resolution images reported in [14];
- 4) Hopfield-type neural network change detection method (Ghosh's method): a modified-Hopfield-neural-network-based context-sensitive technique for unsupervised change detection published in [15].

The first two methods compared in our experiments are the baseline methods used in our proposed approach. The last two methods are all context-sensitive change detection methods. In all these two popular methods, spatial contextual information is fully exploited to improve the change detection performance, which is quite similar to that of our proposed approach.

For fair comparison, in all our experiments, all the initial parameters of the compared unsupervised methods (MRFCDD,

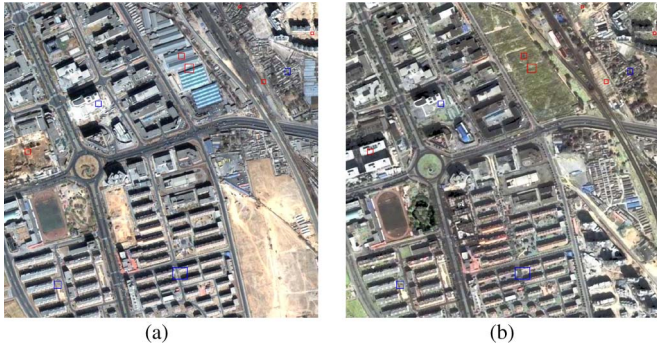


Fig. 2. Beijing data set: (a) Image of 2002 and (b) image of 2003. The positive samples for changed areas are marked with red frames, while the negative samples are represented with blue frames.

Bovolo's, and Ghosh's methods) obtained by unsupervised ways reported in their papers are achieved via supervised training manners with the same training data set.

As exact edge extraction is difficult, in the experiments, a color tensor computed based on invariant derivatives [16] is used as the edge strength between any two adjacent pixels in our proposed approach. The GP classifier in the proposed approach sets both the initial scale and ridge parameters of the radial basis function kernel to one. GP model selection is done by threefold cross-validation. β' is defined according to the literature [9] with a constant smoothness coefficient of one. The high-order inconsistency coefficient θ_s for the MRF model is 0.9. The MRF energy function is optimized by iterated conditional mode algorithm in this letter.

To permit a quantitative evaluation of the effectiveness of the proposed method, a reference map is manually prepared. The validation is measured in terms of the following: 1) false alarm (FA) rate; 2) missed alarm (MA) rate; 3) overall error (OE) rate; and 4) kappa coefficient (kappa) value.

We have tested our proposed approach on several real HR data sets, but for limited space, here, we just report the experimental results on one data set. The Beijing data set is composed of a pair of Quickbird images taken over Beijing (China) on April 9, 2002, and November 12, 2003, respectively. The images consist of a panchromatic image (0.61 m/pixel) and multispectral images (2.4 m/pixel; R/G/B/NIR bands). To achieve both high spatial resolution and spectral resolution simultaneously, the panchromatic image and the multispectral images were fused in a preprocessing step. The sharpened pseudocolor images with 1024×1024 pixels are shown in Fig. 2(a) and (b). The two images were acquired with different sensor acquisition geometries and seasons, and the main changes of the two temporal images are the alterations of land cover. The reference change map is shown in Fig. 3(f).

For the Beijing data set, only 5125 labeled pixels (about 0.49% of the total samples) are chosen as the training samples. The positive samples are marked with red frames, while the negative samples are represented with blue frames in the original multitemporal images shown in Fig. 2(a) and (b).

Fig. 3 shows the change maps produced by all the testing methods, and Table I reports the quantitative analyses results. From Fig. 3(a) and (b), we can find that the two baseline methods are not very effective for HR change detection. Although

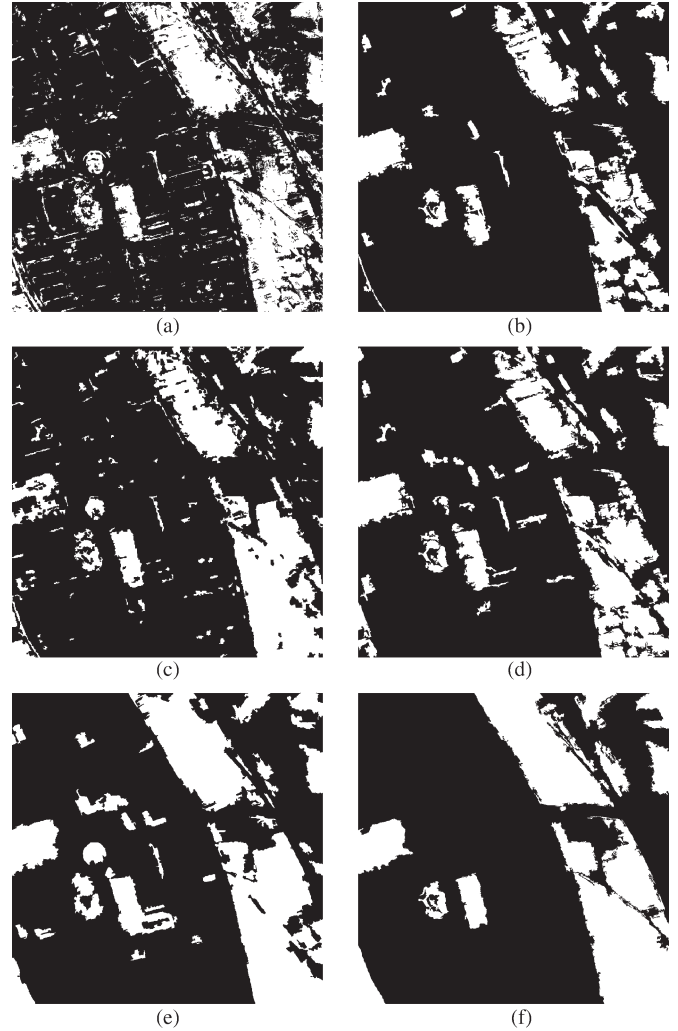


Fig. 3. Change maps on Beijing data set obtained by (a) GPCD, (b) MRFC, (c) Bovolo's, (d) Ghosh's, and (e) S^2CS -GP methods. (f) Reference change map.

TABLE I
SUMMARY OF THE QUANTITATIVE EVALUATION FOR BEIJING DATA SET

	FA(%)	MA(%)	OE(%)	Kappa
GPCD	5.27	7.11	12.38	0.68
MRFC	4.44	10.69	15.13	0.59
Bovolo's	2.62	8.02	10.65	0.71
Ghosh's	3.20	8.71	11.91	0.68
S^2CS -GP	5.45	4.15	9.60	0.76

postprocessing is done (isolated regions with less than six pixels are regarded as noise and removed), GPCD still suffers from serious noise due to lack of spatial context information. Many small regions are falsely detected, which renders the OE rate higher than 11%. The reason is that GPCD performs detection based on single pixel but neglects the spatial correlation among neighboring pixels, which is not robust to the effects caused by alterations of sensor acquisition angles and seasons for HR images. For the MRFC method, although the MRF model has already considered the contextual information during the detection process, the change map in Fig. 3(b) is not as robust as what we expect. The MA rate in Table I is as high as 10.69% and the OE rate is 15.13%, as the MRFC

method performs change detection on the base of maximum likelihood estimation which is not as powerful as the kernel-based classifier. Moreover, spatial context information from only the two-order neighborhoods is considered, so MRFC has the limited expressive power of the complicated scene in HR images. Unfortunately, because of the differences in sensor acquisition geometry and seasonal spectral signatures, a lot of regions are incorrectly detected as changed areas by the maximum likelihood classifier at the initial step. These misclassified regions are so large that their true labels cannot be reconstituted by pixel-based MRF regularization. A better understanding of the effectiveness of the proposed technique can be gained according to the results shown in Fig. 3(c)–(e). By including the spatial contextual information in multilevel parcel-based feature vectors, Bovolo's method behaves well. The kappa coefficient is barely a little lower than that of the proposed approach, and the FA rate in Table I is the lowest for all the compared methods. However, the features obtained by computing the mean on the parcels at different scales are not robust for false changes caused by different view angles. Additionally, the principal component analysis and *k-means* clustering algorithms are also not powerful enough. Based on the neural network classifier, Ghosh's method model the spatial correlation between neighboring pixels, but the pixel-level method is not robust enough for HR image change detection. Fig. 3(e) shows the change map achieved by our proposed approach. Compared with all the other change maps, the change map of S²CS-GP offers a more accurate result. According to visual comparison, many changes caused by noise are removed, and errors caused by the different sensor acquisition angles of the bitemporal images are observably depressed. The kappa coefficient increases to 0.76, and the OA rate is decreased to 9.60% from 12.38% for the GPCD method.

The improvement of the proposed approach mainly owes to the following three facts. First, adaptive second-order MRF potential about edge information is more effective to depress the isolated noise. Second, region-entity-based high-order MRF potential is suitable for HR image change detection and is powerful to remove the false changes caused by different sensor acquisition angles. Third, semisupervised GP classifier is effective to separate the changes from unchanges, which provides a good initialization for MRF regularization.

The proposed S²CS-GP algorithm improves the change detection accuracies with the MRF regularization, but the MRF regularization step also increases the computing time when compared with GPCD. Fortunately, the increment is neglectable. As the MRF regularization is performed on the foundation of the GP classifier output which can be regarded as a very good initialization for MRF regularization, the MRF regularization converges quite quickly. Therefore, the overall computational cost of our proposed method is much less when compared with MRFC.

IV. CONCLUSION

In this letter, a novel semisupervised context-sensitive technique for change detection in HR multitemporal images has been proposed. The proposed approach is composed of a

GP-based semisupervised initialization and an MRF regularization. The initialization step exploits both labeled and unlabeled data based on a semisupervised GP classifier. The MRF regularization aims at properly making full use of the spatial context information by defining a penalty function about the edge strength and incorporating a high-order potential into the traditional MRF model. The experimental results obtained on different real multitemporal data sets confirm the effectiveness of the proposed approach.

The main drawback of the proposed approach is that the edge strength information is not easy to be computed correctly. Thus, further development of this method is to find a proper way to produce an index map helping the MRF model smoothness coefficient automatic selection. Additionally, developing an object-level change detection instead of the pixel-level one in the step of GP initialization is also an interesting work, which may be helpful to save much computing cost for GP classifiers.

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