SIMULTANEOUS CHANGE REGION AND PATTERN IDENTIFICATION FOR VHR IMAGES

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ABSTRACT

Very high resolution images are promising for detecting change regions and identifying change patterns. However, the low overall separability makes it difficult to discriminate change features. In this paper, a framework is proposed to simultaneously detect change regions and identify change patterns. A supervised approach is illustrated within this framework, which is aimed at reducing the overlaps between change classes by capturing the interclass difference and the intraclass similarity. Experiments demonstrate the effectiveness of the proposed approach.

***Index Terms*—** Change detection, Change pattern, Feature classification, Feature transformation, Distance tuning.

1. INTRODUCTION

Detecting changes from multi-temporal images has been the hot topic of remote sensing domain during the recent years. With the development of very high resolution(VHR) satellites(e.g., QuickBird 2 and WorldView 2), change detection receives extensive attentions. Besides detecting change regions, change types(or patterns) can also be recognized by taking advantages of the improved spatial resolution. However, the spatial resolution improvement enlarges the difference between low-to-moderate resolution(LMR) images and VHR images, and this difference makes VHR image change detection more challenging. Specifically, the difficulties of VHR images change detection lie in the following aspects:

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1) Low separability of change features[1, 2]. For LMR images, changes are mainly characterized by spectral differences, and objects can be reliably encoded by spectral responses. However, for VHR images, due to the low interclass variability within an image (e.g., region A vs B in Fig. 1(a)) and the high intraclass difference across images(e.g., region C in Fig.1(a) vs region D in Fig.1(b)), it is difficult to separate the changed class from the unchanged class.

2) Ignorance of user-specific interests[3]. Most of the traditional approaches take less care of user-specific interests. In fact, some types of changes(e.g., region E and F in Fig.1(a)) are salient in the appearance variation, but they are not of user's interests and should be considered as the unchanged class.

To address the above difficulties, in this paper, a novel framework named **SCRAPI**(**S**imultaneous **C**hange **R**egion **A**nd **P**attern **I**dentification) is proposed for VHR images, which integrates two coherent tasks seamlessly, change region detection and change pattern identification. Different from the traditional approaches, SCRAPI aims at projecting each change pattern into a compact cluster and improving the interclass discrimination by tuning the distance between change features.

2. SCRAPI: FRAMEWORK AND ILLUSTRATION

Change detection is essentially the procedure to determine the labels of change features. Specifically, let $\boldsymbol{x_i}$ denote the change feature from the ith element, and y_i denote the label, respectively. $y_i = 0$ means the unchanged class, and $y_i = k(k > 0)$ means the ith change pattern. The key to change detection is to reduce the overlap(e.g., Fig. 1(d)) and

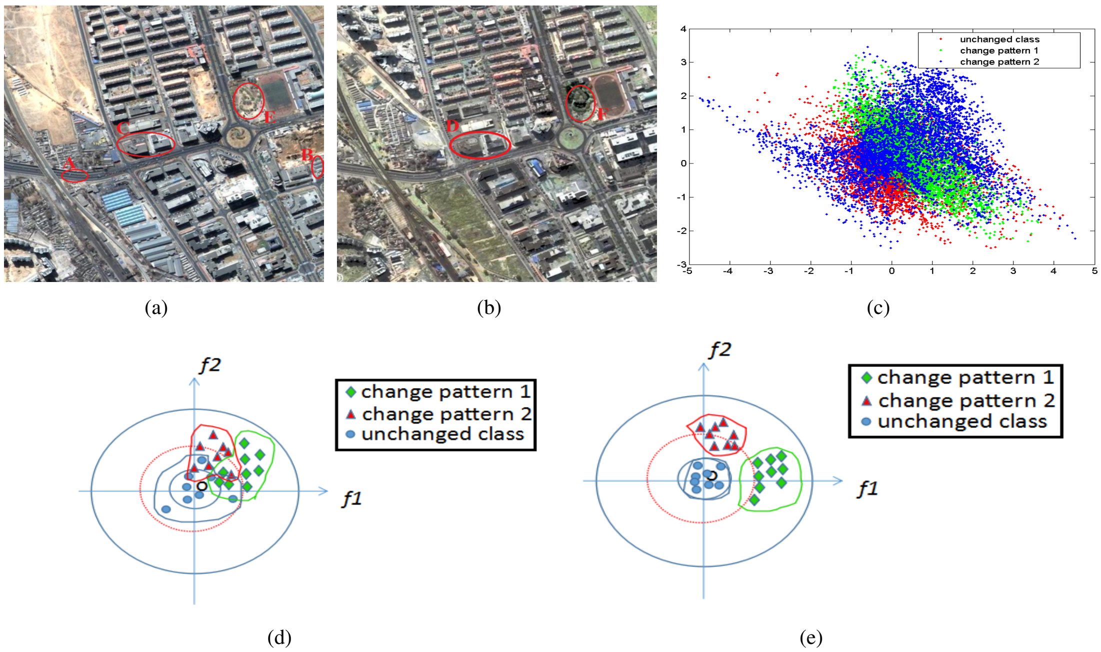

Fig. 1. Illustrations of difficulties in VHR image change detection. (a) and (b): Multi-temporal images, (c): Change feature distributions of unchanged class and different change patterns. (d): Illustration of high overlaps between classes. (e): Illustration of the overall separability improved by the proposed approach. In Figs.1 (c)-(e), for visualisation, high dimensional change features are projected into 2d feature space.

learn a decision function $f(\cdot)$.

2.1. SCRAPI Framework

Despite the promising performance of local features(e.g., HOG(Histogram of Gradients), DAISY[4]) in representing complex objects, the direct feature comparison will result in the high intraclass difference due to the nonlinear mapping between multi-temporal images. For this reason, change features are transformed by the discriminative projection.

In this paper, SCRAPI aims to jointly detect change regions and identify change patterns by learning the projection:

$$\min_{D} r(D) \tag{1}$$

$$s.t.\ \ d(D\boldsymbol{x}_i, \mathbf{0}) \leq \tau_1, \text{if } y_i = 0. \tag{2}$$

$$d(D\boldsymbol{x}_i, \mathbf{0}) > \tau_2, \tau_2 > \tau_1, \text{if } y_i > 0. \tag{3}$$

$$d(D\boldsymbol{x}_i, D\boldsymbol{x}_j) > \tau_3, \text{if } y_i > 0, y_j > 0, \text{and } y_i \neq y_j. \tag{4}$$

Where $r(D)$ denotes the constraint on D, for instance, the sparsity. $d(\boldsymbol{a}, \boldsymbol{b})$ is the distance between vectors $\boldsymbol{a}$ and $\boldsymbol{b}$. Eqs. (2) and (3) are expected to separate the changed class from the unchanged class, and Eq. (5) is expected to discriminate change patterns.

The above framework can be implemented in an unsupervised manner if no training samples are available. However, an implicit assumption about Eqs. (2) and (3) is that the clustering center of the unchanged class is near the origin, $\mathbf{0}$. However, the false changes caused by misregistration or the changes that are not of user's interests are far from the origin. Considering the violation of the unchanged class from the origin and the high overlaps between the changed and unchanged class, it is difficult for the unsupervised strategy to separate mixed change features without extra priors. In other words, the high overlap between different change classes can be significantly reduced by utilizing training samples.

In the supervised context, there are no differences between the unchanged class and the other change patterns, and the SCRAPI framework can be described as:

$$\min_{D} r(D) \tag{5}$$

$$s.t.\ \ d(D\boldsymbol{x}_i, D\boldsymbol{x}_j) \leq \epsilon_m, \text{if } y_i = y_j = m. \tag{6}$$

$$d(D\boldsymbol{x}_i, D\boldsymbol{x}_j) > \tau_{m,s}, \text{if } y_i = m \neq s = y_j. \tag{7}$$

Where $\{(\boldsymbol{x}_i, y_i)|i = 1, \cdots, N\}$ are training samples, and N is the number of training samples.

2.2. SCRAPI Illustration

For illustration, a novel approach is presented within the SCRAPI framework:

$$\min_{W,\xi} \frac{1}{2}\|WW^T\|_{(2,1)} + \lambda \sum_i \xi_i \tag{8}$$

$$s.t.\ \ h_{i,j}(\|\tilde{\boldsymbol{x}}_i - \tilde{\boldsymbol{x}}_j\|_2^2) \geq 1 - \xi_l, \tag{9}$$

$$\tilde{\boldsymbol{x}}_i = W\boldsymbol{x}, \tag{10}$$

$$\xi_l \geq 0, \forall l. \tag{11}$$

Where $h_{i,j} = -1$ if $y_i = y_j$, and $h_{i,j} = 1$ if $y_i \neq y_j$. Eq. (9) is aimed at enlarging the distance between different classes and enhancing the similarity within the same class. For convenience, we set $\tilde{\boldsymbol{x}}_l = \tilde{\boldsymbol{x}}_i - \tilde{\boldsymbol{x}}_j$ and $h_l = h_{ij}$. $\|Q\|_{(2,1)}$ means the mixed $(2,1)$-norm, it is obtained by firstly computing the 2-norm of across the rows of Q_i, and then the 1-norm of the vector $v(Q) = (\|Q_1\|_2, \cdots, \|Q_m\|_2)$. Compared with 1-norm, the mixed $(2,1)$-norm is promising in producing a sparse solution while preserving the data structure. Based on some derivations as in [5], the Lagrange dual version of the above problem is obtained:

$$\begin{aligned} &\max_{\alpha} -\frac{1}{2}\sum_{i,j} \alpha_i\alpha_j h_i h_j \boldsymbol{K_D}(\boldsymbol{z}_i, \boldsymbol{z}_j) + \sum_i \alpha_i \\ &s.t.\ \ 0 \leq \alpha_l \leq \lambda, \forall l, \\ &\sum_l \alpha_l h_l = 0. \end{aligned} \tag{12}$$

where $\boldsymbol{K_D}(\boldsymbol{z}_i, \boldsymbol{z}_j) = [\boldsymbol{z}_i^T \boldsymbol{z}_j]^2$. The above problem is a standard quadratic program, and it can be solved by a variety of approaches, such as the interior point method, active set method, etc.

For each change feature $\boldsymbol{x}$ to be classified, k virtual couples $\boldsymbol{zx}_i^{(j)} = (\boldsymbol{x}, \boldsymbol{x}_i^{(j)})$ need being constructed for each change pattern j, where $\boldsymbol{x}_i^{(j)}(i = 1, \cdots, k)$ are the nearest neighbors of $\boldsymbol{x}$ within the training subset of the jth change pattern. For the virtual couple $\boldsymbol{z}$, the label is determined by

$$f(\boldsymbol{zx}_i^{(j)}) = sgn(\sum_l \alpha_l h_l \boldsymbol{K_D}(\boldsymbol{z}_l, \boldsymbol{zx}_i^{(j)})). \tag{13}$$

$f(\boldsymbol{zx}_i^{(j)}) = -1$ means that the label of $\boldsymbol{x}$ is the same as $\boldsymbol{x}_i^{(j)}$. The final label of $\boldsymbol{x}$ is determined by voting on the above $k*n$ decisions, where n is the number of change classes(including the unchanged class).

3. EXPERIMENTS

For space limitation, only the results on one data set are illustrated. Other four classifiers are used for comparison: Bayes classifier, SVM, decision tree[6] and Adaboost. The performance is measured by MA(missed alarms), FA(missed alarms) for each change pattern and OA(overall classification accuracy). The change features are DAISY-feature-based difference[1]. Training samples are generated by randomly choosing 30% of the pixels from the ground truth for each change class, and different approaches used same training samples. The performances are listed in Tab. 1, and the results detected by different approaches are shown in Fig. 2, where two change patterns, the addition and removal of buildings are highlighted in blue and red, respectively.

From Fig. 2 and Tab. 1, it can be inferred that: (1) Bayes classifier is limited in modeling complex change features, and SVM is inadequate to deal with the high overlap between different change patterns. (2) Decision tree and Adaboost are more effective in dealing with high-dimensional change features. For instance, OAs are improved from 78.4% by Bayes classifier, 84.6% by SVM to 89.2% by decision tree and 86.8% by AdaBoost, respectively. (3) As can be observed from Fig.1(h), by the proposed approach, MA and FA are reduced significantly, some errors caused by decision tree and AdaBoost are being corrected by tuning the distance between change features, which is implemented by the projection matrix W. The above comparisons illustrate the advantages of the proposed approach.

4. CONCLUSION

The pure usage of representative feature representation or discriminative feature classification is limited in addressing the difficulties of VHR image change detection. A novel framework is proposed for simultaneously detecting change regions and identifying change patterns, and the effectiveness of the framework is illustrated in the supervised learning. The novelty of the proposed framework lies in the powerful ability

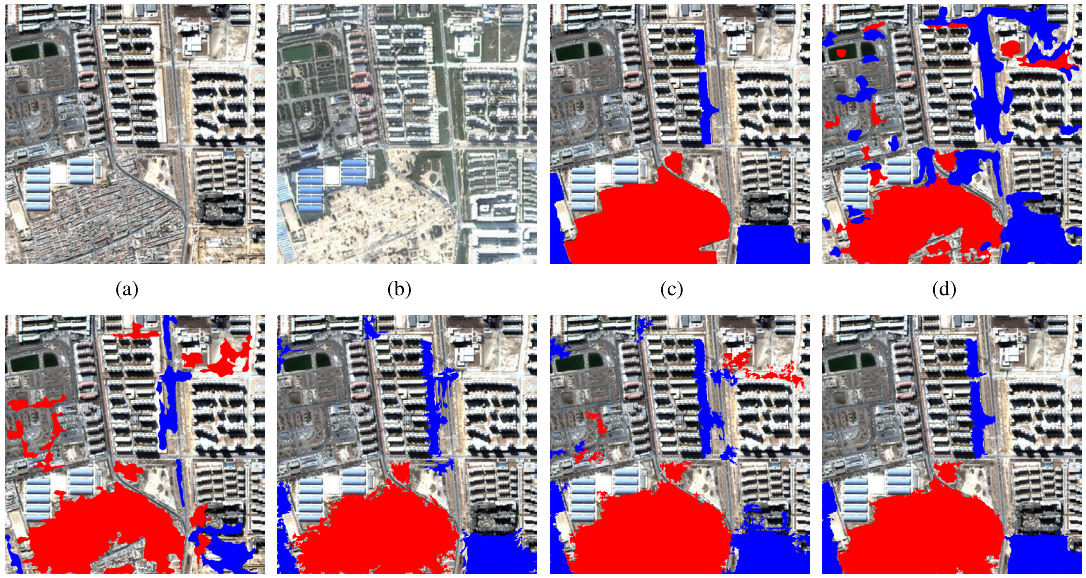

Fig. 2. Change detection result comparison. (a) and (b): Multitemporal images, 1190×1404; (c): Ground truth; (d): Bayes; (e): SVM; (f): Decision tree; (g):AdaBoost; (h):SCRAPI.

Table 1. Performance Comparison

approach	change region		change pattern1		change pattern2		OA(%)
	FA	MA	FA	MA	FA	MA	
Bayes	149440	49632	23165	127731	30583	25827	78.4
SVM	70137	71961	39516	23181	35436	499473	84.6
Decision tree	51812	34816	21324	43460	30016	24876	89.2
AdaBoost	93120	24020	18116	59448	22148	49916	86.8
SCRAPI	32100	15584	12524	22532	15136	21644	94.9

in simultaneously modeling two coherent tasks and learning projection for improving the interclass variability. Our future work will focus on enhancing the interclass separability by other advanced techniques such as multiple kernel learning.

5. REFERENCES

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