A hybrid change detection analysis using high-resolution remote sensing image

Q Q Xu[1,2], Z J Liu[1], M Z Yang[2], H C Ren[1,2], C Song[1,3] and F F Li[1,4]

1 Institute of Photogrammetry and Remote Sensing, Chinese Academy of Surveying and Mapping, Beijing 100830, China
2 Lanzhou Jiaotong University, Gansu Provincial Engineering Laboratory for National Geographic State Monitoring, Lanzhou 730070, China
3 China University of Geosciences, Wuhan 430074, China
4 School of Geomatics Liaoning Project Technology University, Fuxin 12300, China

E-mail: xuqiangqiang2014@foxmail.com

Abstract. In order to reduce noise and improve the accuracy of the final change results, in this paper, we presented a hybrid change detection method based on combining pixel- and object-schemes, Firstly, the method obtained the orthogonal difference images using the pixel-based iteratively reweighted multivariate alteration detection (IR-MAD) algorithm, additionally in the process of iterative weighting, we applied the regularized scheme to stable the generalized characteristic equation for the multispectral data. Consequently, image segmentation algorithm was used to extract the image objects where the changes occurred. Finally, object-based classification method was applied to determinate the types of changes. In order to validate the effectiveness and feasibility of the proposed approach, a simple case was done by using the Horgos Port local multi-temporal and multispectral high-resolution image data in Xinjiang. Compared to the pixel-level IR-MAD, the experimental results showed that the overall accuracy has been improved, moreover successfully reduced noise and pseudo small changes in the final result.

1. Introduction

With the rapid development of remote sensing technology, the high-spatial resolution imagery has been available from commercial operators, providing unique opportunities for change detection. Compared with the traditional low-resolution images, high resolution images with the richer spatial information and the detail information of the feature are widely used[1]. Land-cover and land-use change information is important because it is widely used in various directions, including deforestation

damage assessment, disasters monitoring, urban outspread, urban planning, and land cover change. Singh[2] defined change detection(CD) as "the process of identifying differences in the state of an object or phenomenon by observing it at different times". The general objectives of the remote sensing image change detection is consist of identifying the geographical location and type of changes, quantifying the changes and assessing the accuracy of change detection results[3-5].

At present, high-resolution remote sensing image change detection mainly use the object-oriented analysis techniques. Chen et al. summarized the state-of-the-art object-oriented change detection methods, including image-object change detection, class-object change detection, multi-temporal-object change detection, and hybrid change detection[6]. The hybrid change detection involved the use of both object and pixel paradigms, which was proposed by Carvalho et al. and the authors concluded that this approach was insensitive to geometric misregistration and atmospheric discrepancies between the multitemporal images[7]. Al-Khudhairy et al. applied pixel-based PCA and image differencing for the high-spatial resolution imagery. The change images were then analysed by an object-based classification method, which improved upon the pixel-based change detection[8]. McDermid et al. and Linke et al. transformed multispectral images into wetness bands, which were effective for detecting forest disturbance. This transformation was followed by a pixel-based image differencing using wetness information with an object-based classification applied to the changed areas[9-10]. Niemeyer et al. reported a similar procedure[11]. However, there is a problem that it is difficult to focus change information by means of the common pixel-based change detection.

In this paper, in order to reduce small and spurious changes which are introduced by the inconsistent delineation of objects, and better focus change information, we combine pixel- and object-based schemes to conduct the change detection for the high resolution remote sensing. The pixel-based iteratively reweighted multivariate alteration detection(IR-MAD) could better focus change information[12], and the orthogonal MAD variables are considered to be very suitable for detecting change of the generalized difference image. In addition, Geographic Object-Based Image Analysis(GEOBIA) is new and evolving paradigm[13]. Therefore, we combine pixel-base IR-MAD and GEOBIA to acquire better change detection result.

2. Method

Based on image preprocessing— the image registration and the relative radiometric correction, we combined pixel-based and object-based schemes—a hybrid change detection for high-spatial resolution remote sensing change detection. Firstly, the IR-MAD variables that represented orthogonal different images for the subsequent processing were produced by the pixel-based IR-MAD algorithm. Consequently, the GEOBIA was applied to extract change object. In the end, the object-based post-classification method was used to obtain the change matrices indicating the "from – to" changes. The overall flow chart was shown in the **Figure1**.
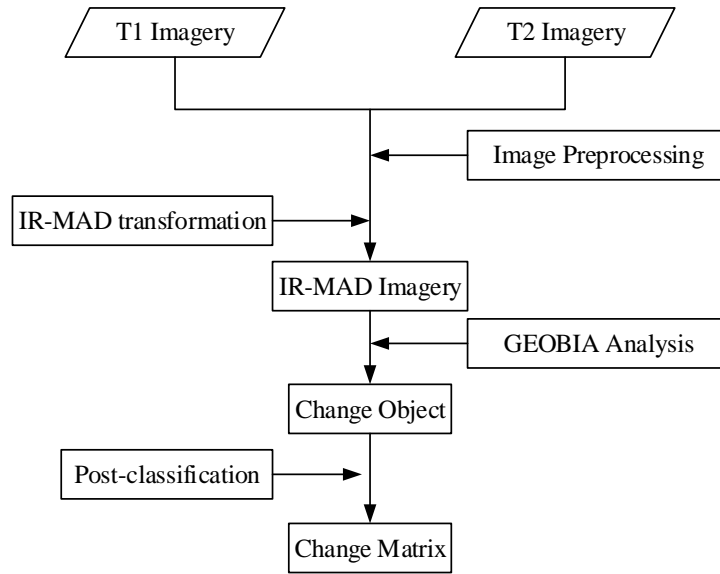
Figure 1. The overall flow chart.

2.1 The pixel-based IR-MAD for obtaining orthogonal different image

The multivariate alteration detection (MAD) algorithm was proposed by Nielsen[14]. The MAD method was based on the canonical correlation analysis (CCA) technique. With the CCA, we could calculate the canonical variates and subtract them from each other. Simultaneously, the canonical variates could be obtained by solving the generalized eigenvalue problem for $p \times 1$ image data X from one point in time and $q \times 1$ image data Y from another point in time ($p \geq q$).

$$\mathbf{a}^T X = a_1 X_1 + \cdots + a_p X_p \tag{1}$$

$$\mathbf{b}^T Y = b_1 Y_1 + \cdots + b_q Y_q \tag{2}$$

or

$$\begin{bmatrix} 0 & \Sigma_{12} \\ \Sigma_{21} & 0 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \rho \begin{bmatrix} \Sigma_{11} & 0 \\ 0 & \Sigma_{22} \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} \tag{3}$$

Among the equation, Σ_{11} is the $p \times p$ variance-covariance matrix of X, Σ_{22} is the $q \times q$ variance-covariance matrix of Y and Σ_{12} is the $p \times q$ covariance matrix between X and Y, other $\Sigma_{21} = \Sigma_{12}^T$. $\mathbf{a}$ is the eigenvector involving the weights with which to multiply X from the one time and $\mathbf{b}$ is also the eigenvector including the weights with which to multiply Y from another time.

In the MAD transformation, by means of maximizing variance, the change information could be focused. Thus, we must minimize the canonical correlation $\rho = Corr\left\{\mathbf{a}^T X, \mathbf{b}^T Y\right\}$. However, we need to get the best coefficients combinations $\mathbf{a}$ and $\mathbf{b}$. A more well-known formulation of the CCA problem

is given by the coupled eigenvalue problems.

$$\Sigma_{12} \ \Sigma_{22}^{-1} \ \Sigma_{21} \ \mathbf{a} = \rho^2 \ \Sigma_{11} \ \mathbf{a} \tag{4}$$

$$\Sigma_{21} \ \Sigma_{11}^{-1} \ \Sigma_{12} \ \mathbf{b} = \rho^2 \Sigma_{22} \ \mathbf{b} \tag{5}$$

In order to conduct the hybrid change detection, we calculate the canonical variates $U_i = a_i^T X$ and

$V_i = b_i^T Y$, and then the MAD change detector as the orthogonal difference image $Z_i = U_i - V_i$. The MAD

variates have variances $Var\{MAD_i\}=Var\{U_i-V_i\}=2(1-\rho_i)$. Hence, the revers ordering which maximizes the

MAD variance $Var\{MAD_i\}$ in the low order MAD variates which are the main differences among the

high order canonical variants.

To build a better background of no-change against which to detect change and make the change information better focus, the iteratively reweighted (IR) scheme had been applied the MAD transformation to put high weighs on observations that exhibited little change over time. The sum of

squared for the standardized MAD variates would approximately follow a χ^2 distribution with p

degrees of freedom, i.e. approximately.

$$T_i = \sum_{i=1}^{p}\left(\frac{Z_i}{\sigma_{Z_i}}\right) \in \chi^2(p) \tag{6}$$

$\sigma_{Z_i} = \sqrt{2(1-\rho_{p-i+1})}$ ideally is the standard deviation of the no-change observations. In the iteratively

reweighted scheme, first start, we assign the same weight (=1) to all pixels. Based on statistics

calculations, we choose to weight pixel j in the next iteration by w_j which is a measure of no change,

namely the probability of finding a greater value of the χ^2 value in Equation 6

$$w_j = P\left\{>\sum_{i=1}^{p}\left(\frac{Z_i}{\sigma_{Z_i}}\right)^2\right\}_j \simeq P\{>\chi^2(p)\} \tag{7}$$

Since the IR-MAD variates are invariant to affine transformation to the original data including linear and affine radiometric normalization or calibration. This makes them well generalized multivariate orthogonal differences among all variables at the two time points of acquisition. Additionally, to solve the ill-conditioned variance-covariance matrices problem and obtain a stable generalized eigenvectors, we apply regularization in CCA.

$$\begin{bmatrix} 0 & \Sigma_{12} \\ \Sigma_{21} & 0 \end{bmatrix}\begin{bmatrix} a \\ b \end{bmatrix} = \rho \begin{bmatrix} \Sigma_{11}+k_1\Omega_1 & 0 \\ 0 & \Sigma_{22}+k_2\Omega_2 \end{bmatrix}\begin{bmatrix} a \\ b \end{bmatrix} \tag{8}$$

where k_1 and k_2 determine the amount of regularization and Ω is designed to minimize as the function

of wavelength.

2.2 Geographic object-based image analysis of image objects

GEOBIA has become a paradigm for remote sensing image analysis. In this paper, we apply the GEOBIA on the IR-MAD orthogonal difference images. Firstly, the IR-MAD images are segmented by the multi-scale segmentation algorithm in the e-Cognition software. Consequently, these features are extracted from the image objects for the segment images, including the geometrical features (width, area and compactness et.al), the spectral features (mean and variance et.al), the texture features (GLCM) and the context information; the Object-oriented change detection is used to the segmented IR-MAD images.

2.3 object-based post-classification for change matrices

In order to obtain the "from-to" change information, namely, the change matrices, we independently classify the IR-MAD image objects, and the classified objects are obtained using the method of supervised classification, moreover to prepare for the further analysis and utilization.

3. Experimental results and analysis

In order to verify the feasibility of the proposed method, The two time ZY3 high resolution satellite image was used for the test in Horgos Port of Xinjiang, the two time original image shown in figure 2.
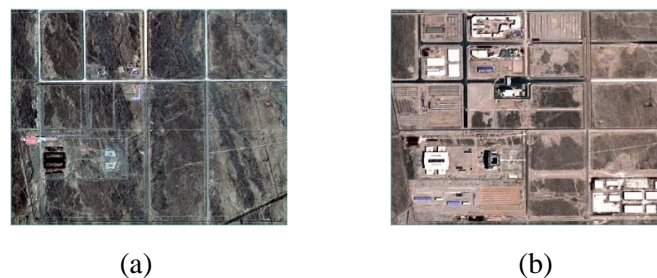

(a)   (b)

Figure 2. 2013 and 2015 ZY3 high-resolution images in the Horgos Port Xinjiang.

Firstly, the IR-MAD orthogonal difference images were obtained by the pixel-level IR-MAD algorithm, the results showed in figure 3 (a). Secondly, these IR-MAD images are segmented and conducted the feature extraction which can be a very good description of the image, the scale level is 60, the results showed in figure 3 (b). Finally, the object-based post-classification change detection results showed in figure 3 (c), which could be seen from the figure. Different colors represented different changes from the bare to other land use class.
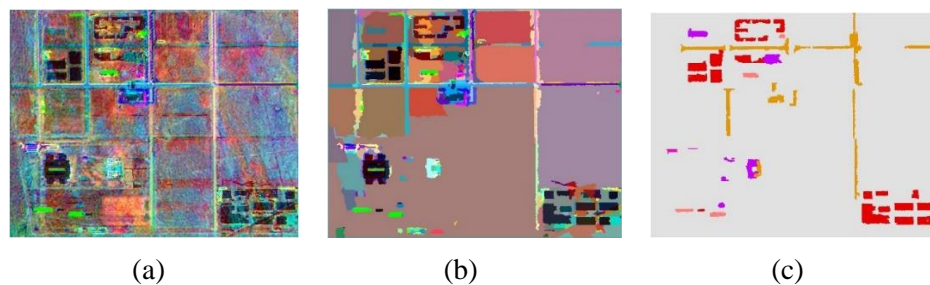

(a)   (b)   (c)

Figure 3. the hybrid change detection results for IR-MAD images(a), segmented images(b) and from-to changes(c).

4. Conclusion and outlook

By combining the pixel-level IR-MAD algorithm and the object-based change detection method, we take full advantage of the pixel-level IR-MAD algorithm to obtain a more focused change information, in addition, by means of the GEOBIA advantage in the analysis of the high-resolution remote sensing images we obtain a better change detection results for the multi-temporal high-resolution remote sensing images. However, there are some problems here, such as the low degree of automation and the error transmission as a result of many steps are involved in the hybrid change detection, it remains unclear how the final change results are influenced by the different combinations of pixel-based and object-based schemes.

5. References

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