An Object-based Change Detection Approach by Integrating Intensity and Texture Differences

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Abstract—**With the development of remote sensing technology, using remote sensing images to do change detection is becoming a hotspot. This paper introduces the research status of pixel-based and object-based change detection technology as well as comments on several change detection methods. A technique for pixel-based change detection by integrating the intensity and texture differences between two frames is studied. An object-based change detection method based on this technique is proposed. Experimental results show that the integrated measure is robust with respect to the illumination changes and noise, the performance of which is outstanding especially when applied to object-based change detection because of pixels' consistency in an object and sharp contrast between objects.**

Index Terms—**Pixel-based, Object-based, Change Detection, Mean Shift, Texture Differences.**

I. INTRODUCTION

The earth's surface changes extremely fast in results of human activities. LandUse change and Landcover change can largely reflect how intensively human beings modify the earth environment and it's the most sensitive indicator of human beings impact on the environment.

Change detection is the process of identifying difference in the state of an object or phenomenon by observing it at different times (singh 1989) [1]. Timely and accurate change detection of Earth's surface features is extremely important for understanding relationships and interactions between human and natural phenomena in order to promote better decision making [1]. Due to the importance of monitoring change of Earth's surface features, research of change detection techniques is an active topic, and new techniques are constantly developed. For example, Image differencing, image rationing, change vector analysis, principal component analysis, post-classification comparison and integration of multi-source data have been used for change detection.

When implementing a change detection project, three major steps are involved: (1) image preprocessing including geometrical rectification and image registration, radiometric and atmospheric correction; (2) selection of suitable techniques to implement change detection analyses; (3) accuracy assessment [1].

Good change detection research should provide the following information: (1) area change and change rate; (2) spatial distribution of changed types; (3) change trajectories of land-cover types; and (4) accuracy assessment of change detection results [1].

The rest of paper is organized as follows. In Section Ⅱ, the research status of pixel-based and object-based change detection technology as well as comments on several change detection methods. Section Ⅲ, a technique for pixel-based change detection by integrating the intensity and texture differences between two frames is introduced. Section Ⅳ, an object-based change detection method based on this technique is proposed. Section Ⅴ, the experiment results are showed and that comparison of pixel-based and object-based change detection analyses. Finally, this paper is concluded in Section Ⅵ with discussions.

II. THE RESEARCH STATUS

With the development of remote sensing technology, using remote sensing images to do change detection is becoming a hotspot and a variety of change detection techniques have been developed, but because of impacts of complex factors, different authors often arrived at different and sometimes controversial conclusions which change detection techniques is most effective. In practice, it is not easy to select a suitable algorithm for a specific change detection analyses and there do not have a change detection techniques suitable to all case now. When study areas and image data are selected for research, identifying a suitable algorithm is important for producing good quality change detection results.

In general, change detection techniques can be grouped into two types: Pixel-based and Object-based. Pixel-based change detection analysis refers to using change detection algorithm to compare the multi-temporal images pixel by pixel while object-based change detection analysis refers to using change detection algorithm to compare the multi-temporal images object by object. However, the definition of pixel-based and object-based change detection is not distinct. The most basic feature of object-based approach is to segment the image and regard the objects as the basic unit of operation, rather than the pixel-based approach regarding a single pixel as the basic unit of operation.

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There have been many pixel-based change detection proposed before such as Image differencing, image rationing which can only provide change/non-change information. These pixel-based change detection techniques are easy to implement, but the threshold which is the key to get good change detection results is difficult to determine. Image differencing is to subtract the first-date image from a second-date image pixel by pixel. It's simple and straightforward, easy to interpret the results, but cannot provide a detailed change matrix and requires selection of thresholds.

One of the limitations of traditional pixel-based change detection approaches is the difficulty to model the contextual information for every pixel by the moving window with the size and shape particular to the corresponding object [2].

To address this problem, many literatures have proposed some different object-based change detection techniques. Wen-jie WANG(2009) presents a way of multi-scale and multi-feature fusion for high resolution remote sensing images change detection. Although this method gets much better results than the traditional pixel-based methods, analysis for choosing optimized object feature is still need to be investigated. Antoine Lefebvre(2008) develop an object-based change detection method able to qualify the nature of changes in landscapes from remotely sensed images, in terms of geometry and content. This method shows its potential advantages in change detection with high resolution images.

III. A ROBUST PIXEL-BASED APPROACH

The pixel-based approach for robust change detection is based upon the integration of intensity and texture differences, and the texture differences is measured based on the gradient vectors between two frames.

Let $p=(x,y)$ be a point in an image plane, $f_i(p)$ be the ith image and $f_i^{'}(p)=[f_i^x(p), f_i^y(p)]$ be the gradient vector which is generated by using the Soble operator. Then the textural difference can be defined as

$$d_t(p)=w(p)\cdot R_t(p) \tag{1}$$

and

$$R_t(p)=1-\frac{\sum_{u\in M_p} 2C_{12}(u)}{\sum_{u\in M_p}(C_{11}(u)+C_{22}(u))} \tag{2}$$

where $C_{ij}(p)$ is the cross-correlation of gradient vectors of two images at p, that is

$$C_{ij}(p)=f_i'(p)\cdot f_j'(p). \tag{3}$$

$C_{ij}(p)$ is the auto-correlation of gradient vectors when $i=j$. Obviously, we have

$$C_{11}(p)+C_{22}(p)\geq 2C_{12}(p). \tag{4}$$

M_p denotes the 5×5 neighborhood centered at p, we normalize $R_t(p)$ by setting $R_t(p)=1$ as the maximum value.

$$w(p)=\begin{cases} 1, & if \quad g_i(p)>2T_w \\ g_i(p)/2T_w, & otherwise \end{cases} \tag{5}$$

where

$$g_i(p)=\max_{i=1,2}\sqrt{\frac{1}{M}\sum_{u\in M_p} C_{ii}(u)} \tag{6}$$

and T_w is a parameter based on image noise distribution that will be determined later.

Let $d(p)$ be the intensity difference of two images, and

$$d_i(p)=\begin{cases} 1, & if \quad |d(p)|>2T \\ |d(p)|/(2T), & otherwise \end{cases}. \tag{7}$$

The parameters T and T_w should be properly chosen to cope with image noise. Since the image noise can be modeled as Gaussian noise following $N(0,\sigma)$, the noise in the intensity difference image has a Gaussian distribution $N(0,\sigma_d)$ with $\sigma_d=\sqrt{2\sigma}$. σ_d may be estimated by the Least Median of Squares(LMedS) method[6]. However, due to the erect of illumination changes, the shifts of gray values of unchanged regions should be compensated to compute σ_d.

First, the shift of gray value at each region is calculated as

$$\bar{d}(p)=\frac{1}{M}\sum_{u\in M_p} d(u) \tag{8}$$

where M is the number of pixels in the region M_p, then the difference image in which gray shifts have been compensated becomes

$$d^{'}(p)=d(p)-\bar{d}(p). \tag{9}$$

Applying the LMedS method to image $d^{'}(p)$ and obtains $\hat{\sigma}_d$, the estimation of σ_d. After this, the mean shift of gray values for unchanged regions is estimated as

$$\bar{d}_s=\frac{1}{\|N_s\|}\sum_{p\in N_s}\bar{d}(p) \tag{10}$$

with

$$N_s=\{p:(|d'(p)|<2\hat{\sigma}_d)\wedge(|d'(p)|<T_{50\%})\} \tag{11}$$

where $T_{50\%}$ is the median of $|\bar{d}(p)|$ and $\|N_s\|$ is the number of points in the set N_s.

Then, the parameter T can be chosen as $\left|\bar{d}_s\right| + 3\hat{\sigma}_d$ and T_w can be chosen as $5\hat{\sigma}_d$.

The textural difference and the intensity difference have defined above. Due to noise and illumination changes, the texture difference is regarded as more reliable and robust than the simple intensity difference. Hence, one should depend on $d_i(p)$ only if the corresponding region has no texture. We can integrate intensity and texture differences as

$$d_{it}(p) = w_i(p) \cdot d_i(p) + w_t(p) \cdot d_t(p) \quad (12)$$

where $w_i(p) = 1 - w(p)$ and $w_t(p) = w(p)$. $d_{it}(p)$ would be within the range of [0,1] and the changes can be detected by thresholding $d_{it}(p)$ at mid-point(0.5).

IV. AN OBJECT-BASED CHANGE DETECTION METHOD

In this method, we extract homogeneous regions from images by using segmentation techniques based on Mean shift (Comaniciu and Meer, 2002) [7].Image segmentation, decomposition of a gray level or color image into homogeneous tiles, is arguably the most important low-level vision task [7].

The mean shift algorithm is a nonparametric clustering technique which does not require prior knowledge of the number of clusters, and does not constrain the shape of the clusters. Let $x_i\ i = 1, \ldots, n$ be the d-dimensional input image pixels in the joint spatial-range domain, and the mean shift is

$$m_h(x) = \frac{\sum_{i=1}^{n} x_i g\left(\left\|\frac{x - x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{x - x_i}{h}\right\|^2\right)} - x \quad (13)$$

where

$$g(y) = \begin{cases} 1 - y, & if \quad |y| \le 1 \\ 0, & otherwise \end{cases}, \quad (14)$$

$$y = \left\|\frac{x - x_i}{h}\right\|^2 \quad (15)$$

and h can be regarded as the spatial h_s defining the spatial window and the spectral h_r defining the spectral window.

Mean shift algorithm estimates the local density gradient of similar pixels. These gradient estimates are used within an iterative procedure to find the peaks in the local density. All pixels that are drawn upwards to the same peak are then considered to be members of the same segment [8].

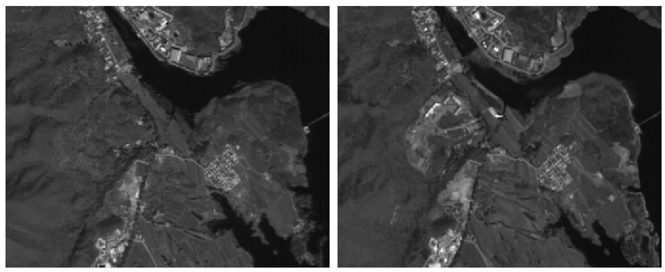
When the homogeneous regions of images are extracted, we consider these regions as 5×5neighborhood in the pixel-based approach, and then implement the pixel-based approach. The good segmented result is the key to produce good quality change detection results. In practice, we get the good regions by setting the suitable parameters h_s , h_r and M which is the least numbers of pixels in spatial regions.

The originality of this method consists in implementing the robust pixel-based approach to objected-based change detection.

V. EXPERIMENTAL RESULTS

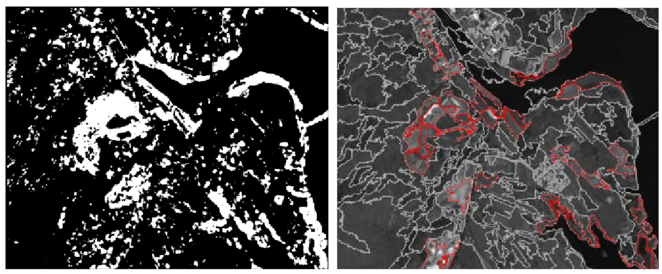
In order to evaluate the proposed approach, experiments were conducted on both panchromatic images and color images. In this section, some experimental results will be given to demonstrate the performance of the technique. The panchromatic data set is composed of two panchromatic image of 613×496 pixel (3m per pixel), which is acquired over Beijing (China) by CBERS-2 in 2005 and 2008. Figure 2(a) show the result of pixel-based change detection and the white pixels represent change region while the black pixels represent non-change region and the region can not be attached to the objects. Figure 2(b) show the result of object-based change detection, and the regions with white edge are non-change areas while the regions with red edge are change areas. The mean shift algorithm is used in Figure 2(b) with the parameters $h_s = 7, h_r = 6.5$.

Figure 3 (a) and Figure 3(b) show the different temporal color images of 600×400 pixel(2.5m per pixel) which is acquired over Tianjing (China) by SPOT5 in 2008 and 2009. Figure 4(a) and Figure 4(b) show the results by the object-based change detection approach, in which the red lines mark the edge of the changed objects.



(a) (b)

Figure 1. Panchromatic data sets used in this paper.

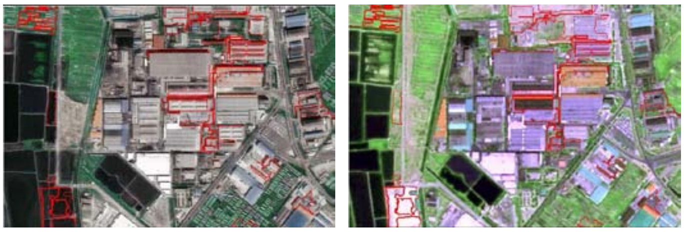


(a) (b)

Figure 2. (a) Result of pixel-based change detection. (b) Result of object-based change detection.

(a) (b)

Figure 3. Color data sets used in this paper.



(a) (b)

Figure 4. Results of object-based change detection.

VI. CONCLUSIONS

In this paper, we introduce a pixel-based change detection technique by integrating the intensity and texture differences and propose an object-based change detection method based on this technique. The object-based change can provide a better means for change detection than a pixel-based method because it provides an effective way to incorporate spatial information and other knowledge into the change detection process. The pixel-based change detection techniques generally only generate change and non-change maps while the object-based change detection not only locates the changes, but also is related to the objects. Although our method is more effective and robust than traditional pixel-based method, we still need to do further work to improve it in the future. Analysis for choosing optimized texture difference will be sequentially investigated and the results of change detection when implementing this method to color images or multi-spectral images.

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