A NEW APPROACH TOWARD OBJECT-BASED CHANGE DETECTION

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ABSTRACT:

Object-based change detection has been the hotspot in remote sensing image processing. Mean shift procedure, a non-parametric feature space analysis technique, is elaborated and used to segment images. A change detection approach is proposed, which is based on the integration of objects' intensity and texture differences. Experiments are conducted on both panchromatic images and multi-spectral images and the results show that the integrated measure is robust with respect to illumination changes and noise. A complementary color detection is conducted to determine whether the color of the unchanged objects changes or not when it comes to multi-spectral images.

1 INTRODUCTION

Change detection is the process of identify differences in the state of an object or phenomenon by observing it at different times (Singh 1989). Timely and accurate change detection of Earth's features provide the foundation for better understanding relationships and interactions between human and natural phenomena to better manage and use resources (Lu et al. 2004).

There have been a lot of conventional pixel-based change detection methods proposed before such as image regression, change vector analysis, principle component analysis. One of the limitations of these 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 (Blaschke and Strobl 2001).

Object-based change detection is a kind of post-classification change detection. Image segmentation is the process of imitating classification and it is crucial to the subsequent tasks. Mean shift procedure was proposed in 1975 by Fukunaga and Hosteler, which was developed by Comaniciu and Meer in 2002 to do feature space analysis and image segmentation. The integration of intensity and texture differences was proposed in 2002 by Li and Leung to do pixel-based change detection. In this paper, a change detection approach based on integration of objects' intensity and texture differences is proposed.

The paper is composed of five sections. Section 2 describes the mean shift segmentation procedure. Section 3 presents a detailed description of the proposed integration of texture and intensity differences for object-based change detection. Section 4 reports the experimental results on panchromatic images and multi-spectral images respectively. Section 5 draws the conclusions of this paper.

2 MEAN SHIFT SEGMENTATION

Since the proposed change detection approach is object-based, the first step should be image segmentation, which is the process of partitioning a digital image into multiple objects.

2.1 Image Segmentation

The goal of segmentation is to simplify or change the representation of an image into something that is more meaningful or easier to analyze. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics.

2.2 Mean Shift Procedure

Mean shift is a procedure for locating stationary points of a density function given discrete data sampled from that function. It is widely used in computer vision and image processing.

Kernel density estimation is the most popular density estimation method. Assume that each data point $x_i \in R^d$, $i = 1,...,n$ is associated with a bandwidth value $h_i > 0$. The sample point estimator

$$\hat{f}_K(x) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{h_i^d}k\left(\left\|\frac{x-x_i}{h_i}\right\|^2\right) \quad (1)$$

based on a spherically symmetric kernel K with bounded support satisfying

$$K(x) = c_{k,d}k(\|x\|^2) > 0 \quad \|x\| \le 1 \quad (2)$$

is an adaptive non-parametric estimator of the density at location x in the feature space. The function $K(x), 0 \le x \le 1$, is called the profile of the kernel, and the normalization constant $c_{k,d}$ assures that $K(x)$ integrates to one. The function $g(x) = -k'(x)$ can always be defined when the derivative of the kernel profile $k(x)$ exists. Using $g(x)$ as the profile, the kernel $G(x)$ is defined as $G(x) = c_{g,d}\, g\left(\|x\|^2\right)$.

By taking the gradient of (1) the following property can be proven

$$m_G(x) = C\frac{\hat{\nabla} f_K(x)}{\hat{f}_G(x)} \tag{3}$$

where C is a positive constant and

$$m_G(x) = \frac{\sum_{i=1}^{n} \frac{1}{h_i^{d+2}} x_i g\left(\left\|\frac{x-x_i}{h_i}\right\|^2\right)}{\sum_{i=1}^{n} \frac{1}{h_i^{d+2}} g\left(\left\|\frac{x-x_i}{h_i}\right\|^2\right)} - x \tag{4}$$

is called the *mean shift* vector. The expression (3) shows that at location x the weighted mean of the data points selected with kernel G is proportional to the normalized density gradient estimate obtained with kernel *K*. The mean shift vector thus points toward the direction of maximum increase in the density. The implication of the mean shift property is that the iterative procedure

$$y_{j+1} = \frac{\sum_{i=1}^{n} \frac{x_i}{h_i^{d+2}} g\left(\left\|\frac{y_j-x_i}{h_i}\right\|^2\right)}{\sum_{i=1}^{n} \frac{1}{h_i^{d+2}} g\left(\left\|\frac{y_j-x_i}{h_i}\right\|^2\right)} \qquad j = 1,2,\ldots \tag{5}$$

is a hill climbing technique to the nearest stationary point of the density, i.e., a point in which the density gradient vanishes. The initial position of the kernel, the starting point of the procedure y_1 can be chosen as one of the data points x_i. Most often the points of convergence of the iterative procedure are the modes (local maxima) of the density.

There are numerous methods described in the statistical literature to define h_i, the bandwidth values associated with the data points, most of which use a pilot density estimate (Silverman 1986). The simplest way to obtain the pilot density estimate is by nearest neighbors (Duda et al. 2001).

A robust non-parametric clustering of the data is achieved by applying the mean shift procedure to a representative subset of data points. After convergence, the detected modes are the cluster centers, and the shape of the clusters is determined by the basins of attraction. See (Comaniciu and Meer 2002) for details.

3 OBJECT-BASED CHANGE DETECTION

After segmented by mean shift algorithm, the images are divided into different regions which is namely objects. Then comparison can be made between the corresponding objects.

3.1 Texture Difference

Texture is an important feature for image representation (Li and Leung 2002). It represents the spatial arrangement of pixel gray levels in a region (*IEEE Standard Glossary of Image Processing and Pattern Recognition Terminology* 1990). There are many approaches developed to describe texture feature (Reed and Buf 1993), such as the co-occurrence matrix, Markov random field, and Gabor filters. A good texture difference measure should be able to represent the difference between two local spatial gray level arrangements accurately. The gradient value can be used to measure the local texture difference since it describes how the gray level changes within a neighborhood and is less sensitive to illumination changes. Let $p = (x, y)$ be a pixel in a image plane, then the i th image and the gradient vector at point p can be represented as $f_i(p)$ and $f_i'(p) = (f_i^x(p), f_i^y(p))$ with $f_i^x(p) = \nabla_x f_i(p)$ and $f_i^y(p) = \nabla_y f_i(p)$. Here the partial derivatives are generated using the Sobel operator. For an object region R, a measure of the gradient difference can be defined as

$$R_t(R) = 1 - \frac{\sum_{p \in R} 2C_{12}(p)}{\sum_{p \in R}(C_{11}(p) + C_{22}(p))} \tag{6}$$

where $C_{12}(p)$ is the cross-correlation of gradient vectors of two images at a point p and $C_{ii}(p)$ is the auto-correlation of a gradient vector at a point p. As illustrated in (Li and Leung 2002), this measure is robust with respect to illumination changes and noise.

If an object R in both images are homogenous with low SNR, $R_t(R)$ becomes invalid. This can be concluded from (6) since the denominator of the second term would be small. To tackle this, a validity weight, $w(R)$, for gradient difference at each object is computed. Let

$$g_i(R) = \max_{i=1,2} \sqrt{\frac{1}{M}\sum_{p \in R} C_{ii}(p)} \tag{7}$$

where M is the number of points in the object R. Then

$$w(R) = \begin{cases} 1, & g_i(R) > 2T_w \\ g_i(R)/(2T_w), & otherwise \end{cases} \tag{8}$$

where T_w is a parameter based on image noise distribution that will be determined later. Consequently, one can define

$$d_t(R) = w(R) \cdot R_t(R) \tag{9}$$

3.2 Intensity Difference

Let $d(p)$ be the intensity difference of two images at each point. Then the intensity difference of two images at each object can be defined as

$$d(R) = \frac{1}{M}\sum_{p \in R} d(p) \tag{10}$$

where M is the number of points in R. In order to normalize intensity difference measure into the same range of [0,1] as texture difference measure, we apply a simple slope function defined as

$$d_i(R) = \begin{cases} 1, & |d(R)| > 2T \\ |d(R)|/(2T), & otherwise \end{cases} \qquad (11)$$

The parameters T in (11) and T_w in (8) should be properly chosen to cope with image noise. Since the image noise can be modeled as Gaussian noise following $N(0,\sigma)$, and the noise in the intensity difference image has a Gaussian distribution $N(0,\sigma_d)$ with $\sigma_d = \sqrt{2}\sigma$. The variance of noise σ_d may be estimated by the Least Median of Squares (LMedS) method (Rosin 1998). However, due to the effect of illumination changes, the shifts of brightness values for unchanged regions should be compensated to compute σ_d. The difference image in which brightness value shifts have been compensated becomes

$$d'(p) = d(p) - d(R) \qquad (12)$$

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

$$\bar{d}_s = \frac{1}{\|\Omega\|} \sum_{R \in \Omega} d(R) \qquad (13)$$

with

$$\Omega = \left\{ R : \left(|d'(R)| < 2\hat{\sigma}_d \right) \wedge \left(|d(R)| < T_{med} \right) \right\}$$,where

T_{med} is the median of $d(R)$ and $\|\Omega\|$ is the number of regions in the set Ω, most objects of which come from the unchanged regions. In this work, $T = |\bar{d}_s| + 3\hat{\sigma}_d$ and $T_w = 1.5 \cdot 2\sqrt{3}\hat{\sigma}_d \approx 5\hat{\sigma}_d$ are chosen empirically. See (Li and Leung 2002) for more details about these two thresholds.

3.3 Integration of Texture and Intensity Differences

The texture and intensity differences can complement each other. They are two different views to the difference between two images. A better change detection can therefore be achieved by integrating the information from these two sources. Due to the noise and illumination changes, the texture difference $d_t(R)$ is regarded as more reliable and robust than the simple intensity difference $d_i(R)$. Hence, one should depend on $d_i(R)$ only if the corresponding region has no texture. This can be accomplished by using $w(R)$ to create an adaptive weighted sum as

$$d_{it}(R) = w_i(R) \cdot d_i(R) + w_t(R) \cdot d_t(R) \qquad (14)$$

Where $w_t(R) = w(R)$ and $w_i(R) = 1 - w(R)$. $d_{it}(R)$ would be within the range of [0,1] and the changes can be detected by thresholding $d_{it}(R)$ at mid-point(0.5), which can be considered as a defuzzilization process.

4 EXPERIMENTAL RESULTS

In order to evaluate the proposed approach, experiments were conducted on both panchromatic images and multi-spectral images. In this section, some experimental results will be given to demonstrate the performance of the technique with respect to illumination changes and the presence of different noise levels.

4.1 Experiments on Panchromatic Images

The data set is composed of two panchromatic images of 613*496 pixels(3m per pixel), which is acquired over Beijing(China) by CBERS-2 in 2005 and 2008. Fig.1(a) and Fig.1(b) show the different temporal images. Fig.1(c) and Fig.1(d) show the results by mean shift segmentation, in which the gray lines mark the edge of the objects. Fig.1(e) and Fig.1(f) show the results by the proposed object-based change detection approach, in which the red lines mark the edge of the changed objects.

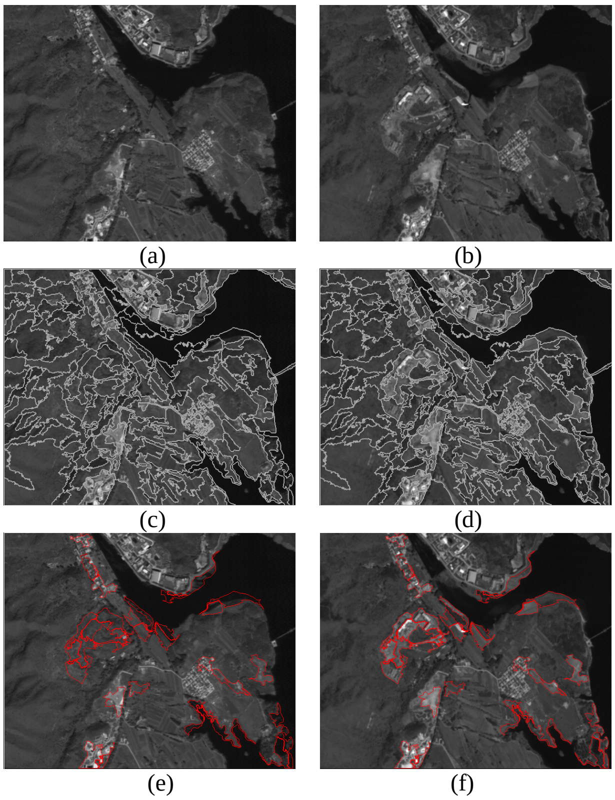

Fig.1. Experimental results on panchromatic images. (a) and (b) are the multi-temporal images. (c) and (d) are the results by mean shift segmentation. (e) and (f) are the results by object-based change detection.

4.2 Experiments on Multi-Spectral Images

Unlike the panchromatic images, some objects of the multi-spectral images are not changed in texture and intensity but changed in color, which can be easily seen. To this problem, a supplementary detection is done by transforming RGB space into L*a*b* space to detect whether the color of the unchanged objects changes or not.

The data set is composed of two multi-spectral images with 3 bands (RGB) of 492*498 pixels(1m per pixel), which is acquired over Chengdu(China) by IKONOS in 2007 and 2008. Fig.2(a) and Fig.2(b) show the different temporal images. Fig.2(c) and Fig.2(d) show the results by mean shift segmentation, in which the gray lines mark the edge of the objects. Fig.2(e) and Fig.2(f) show the results by the proposed object-based change detection approach, in which the red lines mark the edge of the changed objects and the blue lines mark the edge of the color-changed objects.

It is shown from the results that the integrated measure is robust with respect to illumination changes. The color changed objects are mostly of vegetation's seasonal variation.

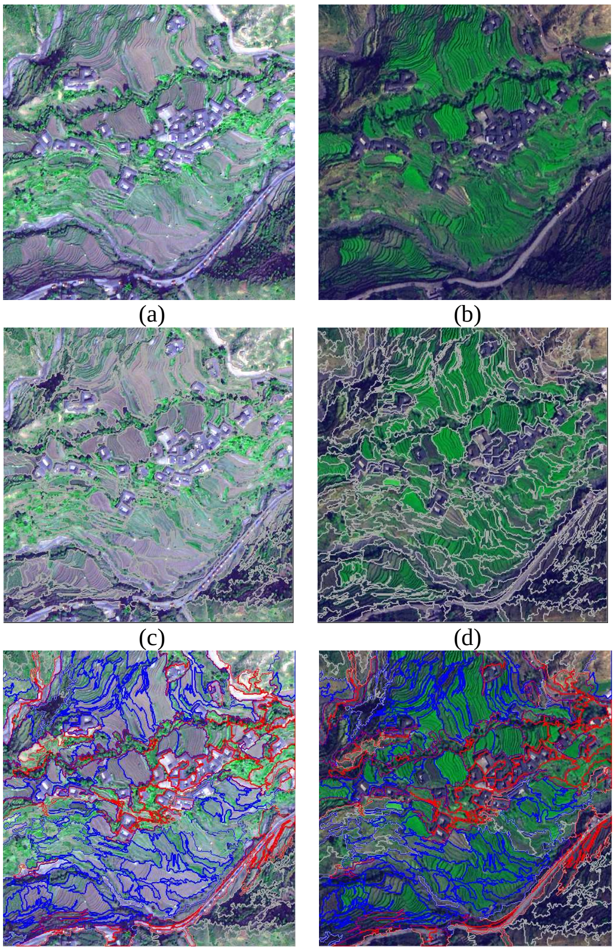

Fig.2. Experimental results on multi-spectral images. (a) and (b) are the multi-temporal images. (c) and (d) are the results by mean shift segmentation. (e) and (f) are the results by object-based change detection.

5 CONCLUSIONS

In this work, the mean shift procedure has been elaborated. The segmentation results show its outstanding performance in image segmentation. The texture and intensity features have been analyzed respectively. The integration of objects' intensity and texture differences for change detection has been investigated. It can be seen from the experimental results that the integrated measure is robust with respect to noise and illumination changes. Currently, when it comes to multi-spectral images, a supplementary color detection is conducted to determine whether the color of the unchanged objects changes or not, which is valuable for monitoring seasonal variation.

Only intensity information of images has been utilized in mean shift segmentation. On next step texture and color information might be considered to support the mean shift procedure in order to obtain better segmentation results.

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