Available online at www.sciencedirect.com
SciVerse ScienceDirect
Procedia Environmental Sciences 11 (2011) 238 – 244
Procedia Environmental Sciences

Change Detection Using Change Vector Analysis from Landsat TM Images in Wuhan

Song Xiaolu[1], Cheng Bo[2]

[1]Center for Earth Observation and Digital Earth Chinese Academy of Sciences Graduate University of the Chinese Academy of Sciences Beijing, China
[2]Center for Earth Observation and Digital Earth Chinese Academy of Sciences Beijing, China
talent_sxl@126.com, bocheng@ceode.ac.cn

Abstract

Spectral Change Vector Analysis (CVA) is based on multi-temporal images. In this paper, a dichotomy search which can be used on detecting changes in the threshold vector is adopted. Meanwhile, a supervised classification technique is used in the direction cosine space with the type of central point in the initial assay vector remote sensing images. Results are discussed in the last part of this paper, which show that CVA can extract change information effectively in our study area of Wuhan city.

Keywords: Change detection; Change vector analysis; Dichotomy; Threshold search; Direction cosine vector space

1. Introduction

Change detection is a process of extracting, analyzing, and defining change information from remote sensing imageries. Usually, change detection refers to discerning the changed areas on two registered remote sensing images at two different times [1]. At present, remote sensing change detection methods are mainly classified into two categories: one based on the spectral characteristics of the type of analysis, and the other is spectral change vector analysis. Spectral characteristics of the type of analysis is based primarily on remote sensing images at the same time using the spectral classification and the calculation to determine the changes in the distribution of information and types of feature [2]. It can be divided into direct comparison, post-classification comparison and multi-spectral transform method. Spectral change vector analysis can avoid not only the classification and time-consuming effort and the accumulated error in the type of unreasonable defect in post-classification comparison method, but also can use more or even all of the bands to detect changes in pixels, and the changes in pixel type information [3] [4].

doi:10.1016/j.proenv.2011.12.037

This paper is based on Spectral Change Vector Analysis (CVA). This method focuses on the analysis of the differences to determine the changes in the characteristics of the strength and direction.

2. Methodology

2.1 Study Area and Data Sources

The study area is located in the north western part of Wuhan, Hubei province, China. It is low and flat with the Fu River winding through the area, including a few lakes and pools. With rich vegetation and clearly recognized artificial coverings, all makes it being a good test area of change detection using remote sensing imageries. In this paper, we use two Landsat TM imageries acquired respectively on July 9, 2002 and April 20, 2005.

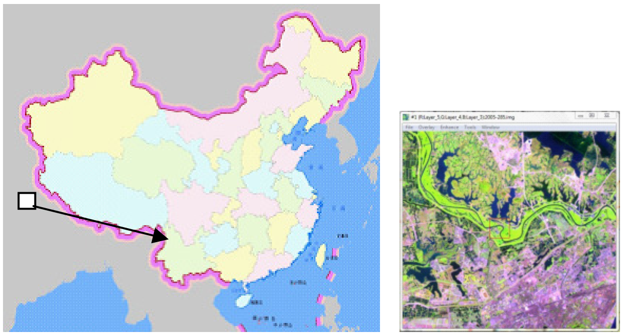


Figure 1 a) China map. b) The study area (at the north west of Wuhan city).

2.2 Image Pre-processing

1) Image co-registration

The key of change detection is to make sure that the location of the same surface features is consistent. If accurate image co-registration is not available, a large area will be found changed because of image misplacement. The essence of image co-registration is image geometric correction, which means unifying images into a normalized coordinate system by geometric transformation according to the geometric characteristics of images.

Image registration usually consists of two steps: 1) determine appropriate image control points. The selection of control points must be as accurate as possible. And enough control points are required to avoid great errors. 2) Register one image to the other using the selected control points.

2) Radiometric calibration

In the processing of remote sensing change detection, we must consider the possible pixel spectral changes caused by other elements, such as soil moisture, vegetation phenology, atmospheric conditions, sun angle, and sensor parameters. These elements' impact on pixel spectral changes must be removed to make sure that the changes are only caused by surface features changes. In this paper, a histogram matching method is used in radiation correction of the experentmental images to eliminate random factors.

2.3 Change Vector Analysis

3) Processing of assistance data

We choose a sub-district A as a typical sample area to determine a threshold which can distinguish the changed pixels from the non-changed pixels in step 1. Figure 2. a) shows the visual discrimination results. Changed pixels are displayed in white, while the black part indicates no change in this area.

Meanwhile, a supervised classification sub-area B is chosen to determine the type of change pixels in step 2. In this paper, four types of change are defined: building, barren, water and vegetation. Land use classes are shown in Figure 2. b). Each gray value refers to a certain land use class as shown in Table Ⅰ: 0 refers to barren(including roads), 100 to building, 175 to vegetation, and 255 to water.

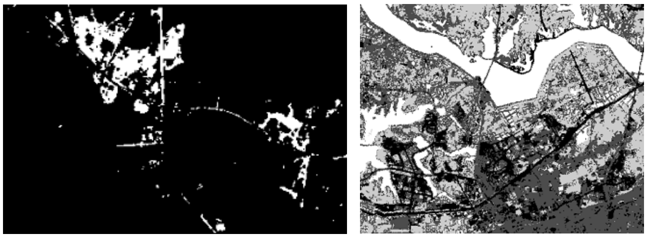


Figure 2 a) Visual interpretation results of sub-area A. b) Land use classes of sub-area B.

Table1 Comparison of gray value and land use class

Color	Gray Value	Land Use Class
	0	Barren
	100	Building
	175	Vegetation
	255	Water

4) Obtaining changed pixels (Step 1)

In CVA, changes are shown as multidimensional spectral vectors, which are accepted as 6-dimensional spectral space from the pair of TM images. For each pixel of each image, it is transferred to a 6-dimensional vector. Where change has occurred in the pair images, the relationship between the corresponding pixels pair can be characterized by a change vector with a measurable strength [5] [6] [7].

Step 1 will distinguish changed pixels from non-changed ones. First, we use change vectors to indicate all the image pixels, which can be seen in (1):

$$\Delta G = G - H \qquad (1)$$

Where k = the number of bands;

$G = (g_1 \quad g_2 \quad \cdots \quad g_k)^T$ = image pixel vector of t1 period, containing 6 bands;

$H = (h_1 \quad h_2 \quad \cdots \quad h_k)^T$ = image pixel vector of t2 period, containing 6 bands;

Then the strength of change is calculated by (2), and we get the angle between each band and its spectral brightness axis using (3):

$$\|G\| = \sqrt{(g_1 - h_1)^2 + (g_2 - h_2)^2 + \cdots + (g_k - h_k)^2} \qquad (2)$$

$$\cos\theta_i = \frac{x_i}{\|X\|} (i = 1,2,3,4,5,6) \qquad (3)$$

Where $X(x_1, x_2, x_3, x_4, x_5, x_6)$ = change vector with 6 bands;

$\|X\| = \sqrt{x_1^2 + x_2^2 + x_3^2 + x_4^2 + x_5^2 + x_6^2}$;

Now we can create a new vector $Z = (\cos\theta_1, \cos\theta_2, \cos\theta_3, \cos\theta_4, \cos\theta_5, \cos\theta_6)$ to determine a certain point in the direction cosine vector space. If a threshold is adopted, it can be used to tell changed pixels from non-changed ones by comparing Z with this threshold value [5].

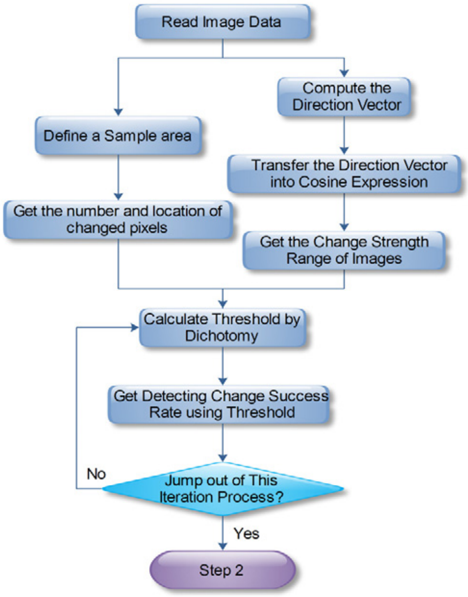


Figure 3 Flowchart of CVA (Step 1).

A key step is how to get this certain threshold value. In this paper, a method using dichotomy is used to obtain a threshold with highest efficacy. Suppose the strength of change ranges between [min, max], the concrete plan is as follows:

a) Choose a proper value P which is small enough according to our accuracy requires.

b) Use T= (min+max)/2 to pick out changed pixels and record their locations and amount.

c) Compare these changed pixels' locations with the visual interpretation results of sub-area A. Then a proportion of the same changed pixels will be calculated, which is referred to as M later.

d) Use T1=T–P and T2=T+P to pick out changed pixels respectively and get the proportion of both, marked by L and R.

e) If L>M, which means T1 can get more changed pixels same as the visual interpretation results of sub-area A, reduce the change range to [min, (min+max)/2]; on the contrary, if R>M, reduce the change range to [(min+max)/2, max].

f) The midpoint of the change range is supposed to be a new T. Continue with this process until we reach a change range which is small enough.

In this area, we get a change strength range of [0, 487.134], and the best threshold is 97.427. Figure 5. a) shows the final change image where changed pixels are displayed in white and non-changed ones in black.

5) Determining change types (Step 2)

In the direction cosine space, given the change classes and their corresponding class center points, we can classify the change pixels with a supervised classification process. After the radiation correction of images on t1 and t2, the spectral change vectors in land use/cover types of one period are supposed to be equal to the spectral difference vectors between t1 and t2 [6]. Based on this approximation, we classify the t1 image accurately and obtain the spectral change vectors between different surface features, whose direction cosine vectors' mean value is equivalent to the classification central points in direction cosine vector space.

Usually, the change classification of each pixel in CVA is computed by the Euclidean distance between each pixel's direction cosine vector and the central points above. One pixel's change class can be determined as the certain class where the minimum Euclidean distance appears.

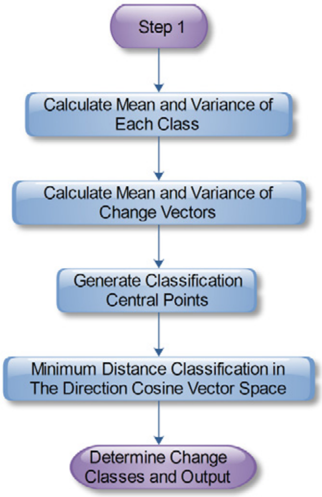


Figure 4 Flowchart of CVA (Step 2).

3. Results

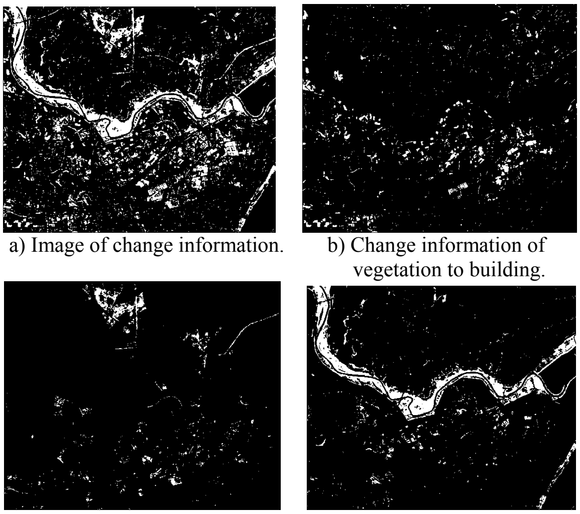
Because only three changing type is effective and practical in practical use, this paper only chooses these three changing directions, including vegetation to building, water to vegetation and vegetation to barren. In addition, there are 37534 pixels changing in the study area, of which 32826 (that is 87.5% of all changed pixels) belong to these three changing directions, so we would only show part of our results as follows.

Table 2 Change information in details by CVA

	CVA	**Number of Total Changed Pixels**	**Percent**
vegetation→building	8,766	32,826	26.70%
water→ve-getation	18,928		57.70%
vegetation→barren	5,132		15.60%

Table 3 Accuracy assessment of CVA method

	CVA	Number of Visual Interpretation pixels	Accuracy
vegetation→building	8,766	9,126	96.06%
water→ve-getation	18,928	21,441	88.28%
vegetation→barren	5,132	5,463	93.94%



a) Image of change information.

b) Change information of vegetation to building.

c) Change information of to vegetation.

d) Change information of water vegetation to barren.

Figure 5 Change information of different types in the study area

4. Discussion And Conclusion

The above three images (Figure 5. b), c), d)) represent three types of change directions. It can be seen from Figure 5 that from 2002 to 2005, the land use/cover change types in Wuhan, mainly occurred as water to vegetation changes, accounting for 57.7% of the total variation. The reason is the time of the 2002 image was obtained on July 9, 2002, when the basin was full of water; the time for 2005 image was April 20, coincided with the spring, when lush vegetation occupied the outer part of the basin. Followed by is the change type of vegetation to building in the urban district of Wuhan, accounting for 26.7% of the total variation. In addition, in the northern mountains there was a considerable number of vegetation developed to city construction land, accounting for 15.6% of total change information.

For monitoring the accuracy of vector analysis, this paper adopts a precision test, whose main method is compared the CVA results with visual interpretation results. The table shows that with a threshold of 97,437, a total of 36,030 pixel changes are correctly detected, which means the change detection accuracy reaches 95.99%. From above we can see that change vector analysis can extract change information effectively after determining a proper threshold by dichotomy.

5. Acknowledgment

This work was supported by the National High-Tech Research and Development Plan of China under Grant No. 2006AA12Z118, the National Natural Resources and Geo-spatial Basic Information Database under Grant No. JCXXK-HT2008-015 and the National Natural Science Foundation of China under Grant No. 60972142. And thanks are due to my colleague LONG Tengfei for assistance with the experiments and for valuable suggestion with this method.

References

[1]Wafa Nori, Hussein M. Sulieman, Irmgard Niemeyer, "Detection of Land Cover Changes in EL Rawashda Forest, Sudan: A Systematic Comparision", International Geoscience and Remote Sensing Symposium (IGARSS), vol. 1, pp. I88-I91, 2009, 2009 IEEE International Geoscience and Remote Sensing Symposium, IGARSS 2009- Proceedings.

[2]ZHANG Zhen-long, ZENG Zhi-yuan, LI Shuo, HU Zi-fu, "A Summary of Change Detection Methods of Remote Sensing Image", Remote Sensing Information, vol. 5, pp. 64-66, 2005.

[3]Jensen J R. Introductory Digital Image Processing, a Remote Sensing Perspective. Prentice Hall, Upper Saddle River, New Jersey, 2nd ED, pp. 197-279. 1996.

[4]R. B. Lorena, J. R. Santos, Y. E. Shimabukuro, I. F. Brown, and H. J. H. Kux, "A change vector analysis technique to monitor land use/land cover in sw Brazilian amazon: Acre state," in PECORA 15-Integrating Remote Sensing at the Global, Regional and Local Scale, Denver, CO, USA, 2002, pp. 8-15.

[5]CHEN Jin, HE Chun yang, SHI Pei jun, CHEN Yun hao, Ma Nan, "Land Use/Cover Change Detection with Change Vector Analysis (CVA): Change Magnitude Threshold Determination", Journal of Remote Sensing, vol. 4, pp. 259-266, May 2001.

[6]CHEN Jin, HE Chun-yang, ZHUO Li, "Land Use/Cover Change Detection with Change Vector Analysis (CVA): Change Type Determining", Journal of Remote Sensing, vol. 5, pp. 346-352, May 2001.

[7]Xingping Wen, Xiaofeng Yang, "Change detection from remote sensing imageries using spectral change vector analysis", 2009 Asia-Pacific Conference on Information Processing, IEEE Press, 2009, doi:10.1109/APCIP.2009.183.