Change Detection in Remote Sensing Images of Damage Areas with Complex Terrain Using Texture Information and SVM

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***Abstract*—Traditional methods, when applied to change detection in remote sensing images of damage areas with complex terrain, often result in inaccuracy. And it is difficult to select an appropriate threshold, which however can be solved by support vector machines (SVM) method. Conventionally spectral information is put into SVM as its features; however, the experimental results are not satisfactory. Considering the spatial distribution and structure information of the image, we choose texture information as the new feature. In this paper, a change detection architecture based on the inclusion of texture information and SVM is proposed. Three textures including simple texture, Tamura texture and GLCM texture are adopted in the experiments. By calculating and comparatively analysing four accuracy specifications which are detection rate, missed alarm rate, false alarm rate and Kappa coefficient, we conclude with the experimental results that GLCM texture accurately reflects the diversity of the regional spatial distribution. The inclusion of appropriate texture information and SVM can be successfully adopted to change detection of damage areas with complex terrain.**

Keywords-change detection; support vector machines; texture feature; earthquake; damage areas; complex terrain.

I. INTRODUCTION

Manual rescue and exploration after the earthquake often delay the best rescue time because of the communication interruption. Nowadays rapidly developing remote sensing technology plays an important role in disaster detection and assessment[1]. Change detection in the remote sensing images before and after earthquake is critical to obtain change information.

There are many change detection approaches and different classification models. Change detection approaches are categorized into (1) comparative analysis of independently produced classifications for different dates and (2) simultaneous analysis of multi-temporal data (Singh A., 1989)[2], which is the first classification model proposed in literature. They are divided into two categories based on image registration and data sources (Deren Li, 2003)[3]. Lu attributed them to seven categories: algebra, transformation, classification, advanced models, GIS, visual analysis and other techniques (Lu D, Mausle，Brondizio E, et al, 2004)[4]. After that a three classification model was proposed which includes intensity-based, feature-based and object-based (Richard J, Radke, Srinivas A et al.,2005)[5]. Now the most common approaches are image differencing, change vector analysis method and principal component analysis, which have achieved some particular results on different occasions.

Pixel-level change detection methods are usually adopted to damage areas, which, however, are only adaptable to cases with simple terrain. Besides, threshold selection is also difficult, and to avoid that we adopted a feature-level support vector machines (SVM) method[6]. Conventionally spectral information is put into SVM as its feature. Since areas with complex terrain have various spatial distributions of spectral values, the detection results turn out to have low performance. Considering the spatial distribution and the structure information of the image can be characterized by texture information, we select it as the input feature and experiment on three different types of textures.

The remainder of the paper is organized as follows: section 2 introduces the experiment on traditional method adapted to areas with complex terrain and the results; section 3 presents a new change detection architecture based on the inclusion of texture features and SVM; section 4 presents experimental results and discussion and section 5 draws the conclusion of the paper.

II. PRINCIPAL COMPONENT DIFFERENCE METHOD

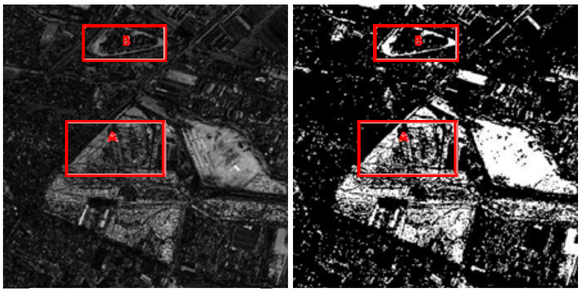
The data used in this paper are two WorldView-2 satellite images of the earthquake damage areas in Port au Prince, Haiti.

(a) before earthquake (b) after earthquake

Figure 1. Remote sensing images before and after Haiti earthquake.

Figure 1 (a) and Figure 1 (b) are the registered images having sub-pixel level. The main change area is the crowd appearing after the earthquake in the middle area of the images. Surrounding buildings are the unchanged area. District A and B in Figure 1 represent typical changed crowd and unchanged buildings respectively.

Figure 2 is the experimental result of principle transform difference method, Figure 2(a) is the difference between two first principle components, in which, the brighter pixels are, the more likely they have changed; the darker pixels are, the less likely they have changed. Figure 2(b) is obtained after thresholding Figure 2(a), and the white pixels illustrate they have changed and the black ones illustrate they haven't.



(a) difference gray image (b)binary image by thresholding (a)

Figure 2. Experiment results by principle component difference method.

In figure 2(b), the left-top part of district A detects the unchanged part correctly. However, the rest of it has amounts of false detected pixels, and many pixels which should be white are identified to be black. Likely, district B has amounts of false detected pixels and they should be black but identified to be white. The results shows in complex terrain the principle transform difference method can't obtain accurate results whether in changed part or unchanged part.

Some typical areas are selected in two-temporal images in order to evaluate the resulting image of principle component difference method quantitatively. In these areas we can easily determine whether they have changed or not (see Figure 3).

(a) before earthquake (b) after earthquake

Figure 3. Typical areas used for specifications calculation

In Figure 3, red-marked areas denote actually changed pixels and the blue-marked areas denote actually unchanged pixels.

In this paper four accuracy specifications are adopted:(1)detection rate is the proportion of correctly detected pixels in all pixels;(2)false alarm rate is the proportion of detected-changed-but-actually-unchanged pixels in all the detected changed pixels;(3)missed alarm rate is the proportion of actually-changed-but-detected-unchanged pixels in all the actually changed pixels;(4)Kappa coefficient reflects the consistency of detection results, which has a range of 0 to 1, and larger value illustrates higher performance.

Threshold is selected by matlab threshold function and the results are illustrated in Table I. As observed from table I, detection rate basically meets the requirement, however, the false alarm rate and missed detection rate are too high, and the Kappa coefficient is too low, which is consistent with the qualitative analysis.

TABLE I. ACCURACY SPECIFICATIONS OF PRINCIPLE COMPONENT DIFFERENCE METHOD

Type of method	Detection rate	False alarm rate	Missed alarm rate	Kappa Coefficient
Principle component difference	86.28%	31.65%	48.85%	0.5049

Besides, we compare the accuracy specifications of different thresholds and depict the change curves as illustrated in Figure 4.

Abscissa denotes thresholds and ordinate denotes false alarm rate and missed alarm rate. Respectively the red solid line and the blue dashed line represent the trends of false alarm rate and missed alarm rate. The effective range which is between two vertical black dashed lines is selected. As observed from Figure 4 false alarm rate and missed alarm rate are inversely related, which suggests they can't reach the minimum at the same time. The analysis implies threshold selection has a great influence on detection results and it is a difficult task to select an appropriate threshold.

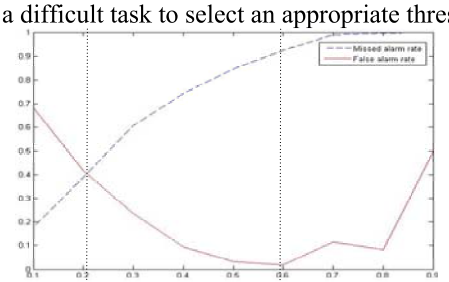


Figure 4. Accuracy specifications trend curves by different thresholds

To avoid the threshold selection, we adopted SVM to change detect remote sensing images with complex terrain.

III. A CHANGE DETECTION METHOD BASED ON THE INCLUSION OF TEXTURE FEATURES AND SVM

More studies adopted SVM as new solutions since it became more difficult for traditional change detection methods to obtain satisfactory results. Since areas with complex terrain have various spatial distributions of spectral values, which can be well reflected by the texture information, it is selected as the feature.

In this paper we select three widely used textures which are simple texture, three features from Tamura texture[7] and four indicators based on gray-level co-occurrence matrix(GLCM)[8].Simple texture is the mean and variance of three-pixels-width fields for each pixel. Others are described below:

A. Tamura texture

i) Coarseness

Find the maximum value in the average graylevel value difference between adjacent windows in the direction of vertical and horizon, and the corresponding value of window size k. The best size $S_{best}(x, y)$ is 2^k :

The formula of coarseness is as follows:

$$F_{crs} = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} S_{best}(i, j) \tag{1}$$

ii) Contrast

Formula is as follows:

$$F_{con} = \frac{\sigma}{a_4^{1/4}} \tag{2}$$

where $a_4 = \mu_4 / \sigma^4$. μ_4 is the fourth moments and σ^2 is the variance.

iii) Directionality

Calculate the gradient vector for each pixel. The magnitude and direction are $|\Delta G|$ and θ ,then construct direction angle local edge probability histogram $H_D(\Phi)$.,at last the final formula is as follows:

$$F_{dir} = \sum_{p}^{n_p} \sum_{\Phi \in w_p} (\Phi - \Phi_p)^2 H_D(\Phi) \tag{3}$$

where p represents the histogram peak, and n_p represents all the histogram peaks. For a certain p, w_p represents the distance between two bottoms next to the peak, and Φ_p is the position of the crest center[9].

B. Gray-level co-occurrence matrix (GLCM)

As $P(i, j)$ is the value in the position of (i, j) for GLCM:

i) Angular Second Moment

$$ASM = \sum_{i} \sum_{j} P(i, j)^2 \tag{4}$$

ii) Contrast

$$CON = \sum_{i} \sum_{j} (i - j)^2 P(i, j) \tag{5}$$

iii) Correlation

$$COR = \frac{\left[\sum_{i} \sum_{j} ((ij) P(i, j)) - \mu_x \mu_y \right]}{\sigma_x \sigma_y} \tag{6}$$

iv) Entropy

$$ENT = -\sum_{i} \sum_{j} P(i, j) \log P(i, j) \tag{7}$$

In order to reduce the impact of difference directions, generally we take 0^{o}、45^{o}、90^{o} and 135^{O} four directions and calculate the indicators for each direction, at last take the average values of them[10].

C. Architecture

The architecture in this paper is illustrated in Figure 5. And the steps are illustrated as follows:

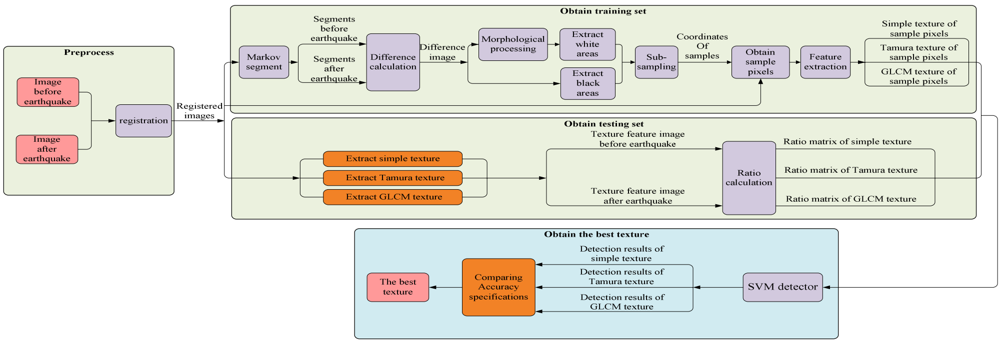


Figure 5. Change detection architecture based on the inclusion of textures and SVM

i) Register bi-temporal original images. It includes geometric registration and radiometric registration, which are respectively achieved by quadratic polynomial method and histogram matching.

ii) Segment each image into two categories by Markov model. Calculate the difference of classified images and do morphological process to the difference image. At last extract coordinates of training samples from the black areas of unprocessed image and the white areas of processed image.

iii) Extract the three textures from pixels in registered images corresponding the coordinates of training samples and put them into SVM.

iv) Extract the three textures from pixels apart from training samples in registered images and put them into SVM to achieve classified results, in which white pixels are changed and black pixels are unchanged.

v) Compare and analysis the accuracy specifications of the final results and select the best texture.

IV. RESULTS AND DISCUSSION

The results are illustrated in Fig.6. We select the same red-marked district A and B as in Figure 2. As can be observed from Figure 6, GLCM texture has the highest performance. In district A, GLCM texture detected the main change areas; in district B, GLCM texture hardly has any false alarms, while Tamura and simple textures have numerous ones. Tamura has higher performance than the simple texture. As observed from the green-marked districts in Figure 6 (b) and Figure 6 (c), Tamura has detected more change areas than simple texture

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(a) simple texture (b) Tamura texture (c) GLCM texture

Figure 6. Binary images for three textures

The reason is there are numerous small details in the experiment images, and GLCM texture can describe them by adjusting the parameters and selecting appropriate pixels distances as well as the number of gray-levels. However, Tamura texture can't do the same and simple texture can't even comprehensively describe texture information only by average values and variances. Qualitative analysis showed among three textures, GLCM texture has the highest performance and simple texture has the lowest performance.

Calculate the accuracy specifications from typical sample districts as shown in figure 3 and the results are illustrated in table II.

TABLE II. ACCURACY SPECIFICATIONS OF FOUR METHODS

Type of method	Detection rate	False alarm rate	Missed alarm rate	Kappa Coefficient
Principle component difference	86.28%	31.65%	48.85%	0.5049
Simple texture	81.25%	49.65%	33.88%	0.4545
Tamura texture	88.13%	32.74%	27.37%	0.6247
GLCM texture	93.85%	12.67%	21.04%	0.7920

As observed from table II, all four specifications of GLCM texture are the optimal. The performance has improved 55.2% than the principle component difference method, 74.26% than simple texture and 26.8% than Tamura texture. GLCM texture is the most applicable among three textures, which is consistent with the qualitative analysis.

V. CONCLUSIONS

In this paper we proposed a new change detection architecture based on the inclusion of textures and SVM. Three textures including simple texture, Tamura texture and GLCM texture are briefly introduced, and put into SVM as features to obtain the experimental results. At last we compare and analyse the accuracy specifications of three textures. The experimental results demonstrated GLCM texture has the highest performance among all. The inclusion of GLCM texture and SVM has significant superiority over traditional methods. Therefore the GLCM texture is suitable for change detection in remote sensing images of damage areas with complex terrain.

The study in this paper has reference value for the feature selection in change detection based on SVM when remote sensing images have damage areas with complex terrain. It also has a good prospect in the earthquake detection and evaluation.

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