Damage Detection Technique based on Texture Analysis

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ABSTRACT

Remotely sensed data have been utilized efficiently for damage detection immediately after the natural disaster since they provide valuable information on land cover change due to spatial synchronization and multitemporal observation over large areas. Damage information obtained at an early stage is important for rapid emergency response and recovery works. Many useful techniques to analyze the characteristics of the pre- and post-event satellite images in large-scale damage detection have been successfully investigated for emergency management. Since high-resolution satellite images provide a wealth of information on damage occurred in urban areas, they are successfully utilized for damage detection in urban areas. In this research, a method to perform automated damage detection is proposed based on the differences of the textural characteristics in pre- and post- high resolution satellite images.

I. INTRODUCTION

Remote sensing is a technique used to obtain information about an area without actually touching and provides acquired measurements of the characteristics of a large area. Remotely Sensed data have been utilized efficiently for damage detection immediately after the natural disaster such as earthquake and flood. Timely and accurate information on damage detection at an early stage is essential for effective and efficient emergency response and recovery works after the event.

Change detection is the process of identifying changes in the state of an object or phenomenon by observing it using multitemporal data sets obtained at different times [1]. It is very useful in many applications such as land cover change analysis, monitoring of pollution, assessment of natural disaster areas, and so on. Changes in land cover usually results in detectable changes in radiance, pattern, or texture values between bi-temporal images. Methods to analyze the characteristics of the pre- and post-event satellite images have been successfully employed for emergency management. Since large areas on the Earth surface is to be analyzed in many cases, it is necessary to make automatic detection process in order to reduce the effort and time. For change detection and mapping, a variety of digital image processing techniques are utilized to characterize and analyze features in the data. The selected processing and analysis techniques could affect the quality of the obtained information.

While the spatial resolution of the satellite images from 20 m to 30 m is difficult to identify the detailed damage such as individual buildings, datasets in high spatial resolution domains (~0.6 m spatial resolution) provide a wealth of information on damage especially in urban areas. Hence, high resolution imagery such as QuickBird has been successfully utilized in many applications to identify even individual buildings in urban areas and to detect damages such as earthquake [5]. Furthermore, the results can be overlaid on geological maps and then analyzed together because the satellite images are georeferenced to standard cartographic projections [4].

In this research, an efficient method to perform damage detection after the natural disaster is studied based on the analysis of the textural characteristics of damaged areas in pre- and post- high resolution satellite images. The algorithm utilizes the difference in neighborhood correlation values between textural measurements of bi-temporal images obtained from wavelet transformation and grey level co-occurrence matrix.

Texture analysis is a fundamental task to many applications, where features for texture representation and characterization are important to analysis and classification. It is a popular technique used to perform spatial analysis in remotely sensed data. Damage detection is one of the application areas of texture analysis. Wavelet transformation is utilized to exploit textural properties between changed and unchanged areas in remotely sensed data of abundant textural information. Statistical features with GLCM combined with wavelet transformation can lead to effective solutions for the texture analysis problems particularly, the damage detection problem [2].

Most damage detection methods are based on the assumption that multitemporal images have been exactly registered, allowing pixel-based comparison. However, in remotely sensed images, differences in distortion are usually inevitable due to different sensor angles and positioning, which makes it very difficult to register two images accurately. The misregistration reduces the accuracy in change/damage detection results. With this reason, window-based detection method is appropriate.

II. ANALYSIS OF TEXTURAL INFORMATION

2.1 Texture analysis using Wavelet Transformation

In the wavelet transform (WT), images are transformed into a multiscale representation with the spatial as well as frequency characteristics, which allows an investigation of textural characteristics at different scales [2]. WT offers the ability of robust feature extraction in images. Then, Statistical features, GLCM, are extracted from the co-occurrence texture matrices from the sub-bands that represent the texture.

By applying WT, an image is decomposed into four sub-images as follows which arise from separate applications of vertical and horizontal filters in shown in Fig. 1,

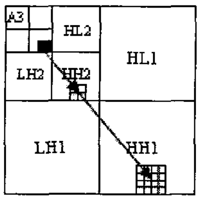


Figure 1 Wavelet decomposition process

where LH, HL, and HH represent the detail images and LL(A) represent approximation image. First L and H refers to a low and high frequency passband in the horizontal direction and the second L and H in vertical direction. WT is repeatedly applied to the approximation image, A(LL), for further decomposition using horizontal and vertical directional filters. Define a series of sub-images decomposed with n level WT as {LH1, HL1, HH1, ... LHn, HLn, HHn, An}. Let W_L represent the wavelet transformed image for an original image of the finite lattice L defined as

$$W_L=\{W_{LH1}, W_{HL1}, W_{HH1}, \cdots W_{LHn}, W_{HLn}, W_{HHn}, W_{An}\} \quad (1)$$

With orthogonal WT, the sub-images provide the non-redundant features to characterize texture. The wavelet decomposition enables to determine the frequency bands carrying the most information about the texture and offers the ability of robust feature extraction in images [2].

2.2 Grey Level Co-occurrence Matrix (GLCM)

Calculation of co-occurrence probabilities is a widely utilized method to extract textural features in remotely sensed data. The co-occurrence features are obtained by using a gray level co-occurrence matrix (GLCM) to store the co-occurring probabilities [2, 3]. In the GLCM technique, the probability of co-occurrence between two grey levels i and j given a relative orientation and distance can be computed for all possible co-occurring grey level pairs in an image window. These probabilities in the GLCM are dimensioned to the number of all grey levels. The elements of a GxG GLCM, P_d, for a displacement vector **d**=(dx, dy) is defined in the following,

$$P_d = |\{(r,s),(t,v): I(r,s)=i, I(t,v)=j\}| \quad (2)$$

where $I(\cdot,\cdot)$ denotes an image of size NxN with G gray values, (r, s), (t, v) $\in$ NxN, (t, v)= (r+dx, s+dy) and $|\cdot|$ is the cardinality of a set.

Then, selected statistics are applied to the GLCM by stepping through the entire matrix to calculate the texture features. Haralick et al. proposed 14 measures of textural features derived from co-occurrence matrix [3]. In this study, the following three image properties are utilized,

1. Homogeniety

$$HOM = \sum_i \sum_j \frac{p(i,j)}{|i-j|} \quad (3)$$

2. Contrast

$$CON = \sum_i \sum_j (i-j)^2 p(i,j) \quad (4)$$

3. Entorpy

$$ENT = \sum_i \sum_j p(i,j) \log p(i,j) \quad (5)$$

In this research, it is studied that the combined texture analysis method of wavelet transformation and GLCM is a more effective approach than the texture analysis with only GLCM. Next, the detection process is applied to the texture feature results to detect damage areas. In the detection part, Mahalanobis distance measure to assign each feature vector a label (damaged or undamaged) is applied and detection map composed of damaged and unchanged undamaged is generated.

III. RESULTS

In this section, the proposed method is tested with some subset of QuickBird images with 0.6m spatial resolution shown in Fig 1: a pre-earthquake image obtained on Sept. 30, 2003, and a post-earthquake image obtained on Jan. 3, 2004. The earthquake of magnitude 6.6 occurred on 26 December 2003 in Bam, Iran [4]. Damage information obtained at an early stage is very important for rapid emergency work. It is notified that there occurred significant damage after the earthquake in Fig. 2 (a) and (b). Pixel-based detection methods are not proper in the case of high resolution images because too many undesirable values are detected as damage which are not real ones. This is because two images can't be superposed exactly due to view angle change of the sensor on the different data-acquisition dates, especially in the areas where tall buildings are located. The difference in shadows of buildings is also an additional difficulty.

The whole correlation coefficients for damaged areas and undamaged areas are compared in Fig. 3. Even though the correlation distribution between pre-earthquake and post-earthquake images shows the difference in damaged and undamaged areas and the average correlation values are quite different in Table 1, it is not enough to distinguish two categories because many damaged and undamaged areas still have similar coefficient values as shown in Fig. 2, which makes it difficult to directly compare neighborhood correlation values.

(a)

(b)

Figure 2 Subset of Quickbird images (a) undamaged areas (b) damaged areas: (Images: curtsey of CSR, University of Texas.)

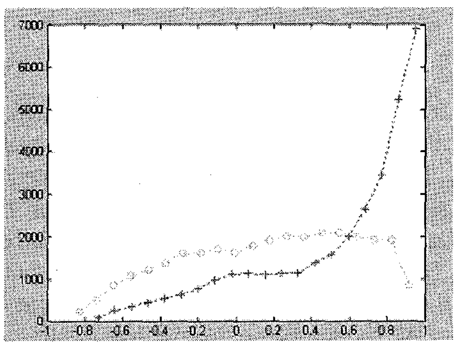


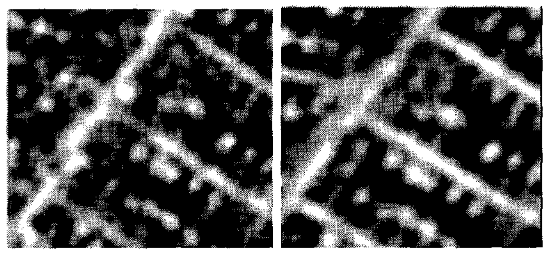
Figure 3 Comparison of the correlation coefficients: red-undamaged areas, Cyan–damaged areas

Table 1. Comparison of the average correlation coefficient values between damaged and undamaged areas

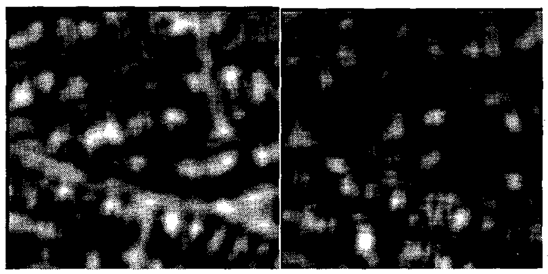
Area Category	Average Correlation
Undamaged areas	0.8139
Damaged areas	0.2587

To solve this problem, WT is employed to pre- and post-images for the textural information, resulting in the sub-bands that represent the texture. Then, the GLCM method of texture analysis is applied to characterize the spatial relationship between a pixel and a neighboring pixel at distance 1 and angle 0°, 45°, 90°, 135° in decomposed sub-bands.

The areas of different texture-related values obtained from WT are considered to be damaged areas. In Fig. 4, textural results between pre- and post- earthquake images in damaged and undamaged areas are compared. The difference in texture after earthquake can be recognized easily in the damaged area.



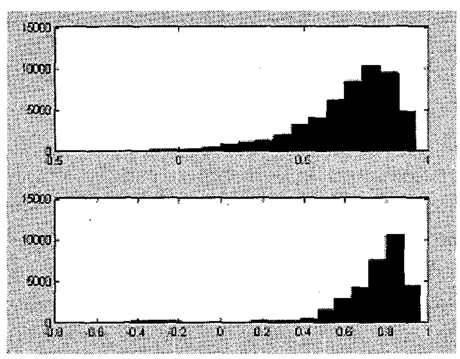
(a) undamaged areas



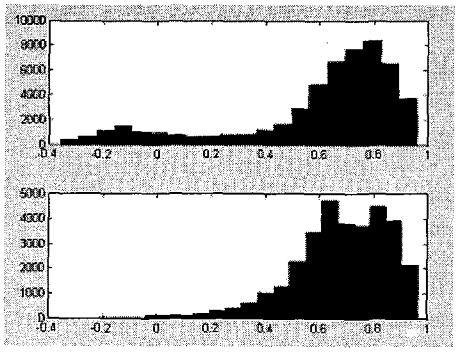
(b) damaged areas

Figure 4 Comparison of textural information from WT between pre-earthquake and post earthquake

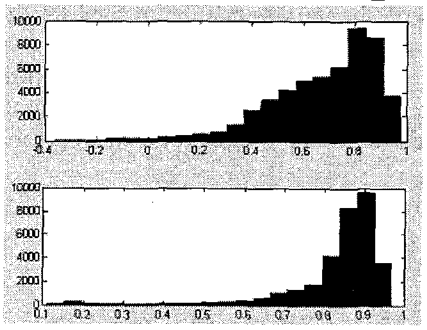
To investigate the effect of WT_GLCM method, the distribution patterns of the correlation values between textural measurements of pre- and post- earthquake images obtained with single GLCM and WT_GLCM method are compared in Fig. 5.



(a) Homogeniety : above-GLCM, below-WT_GLCM



(b) Contrast: above-GLCM, below-WT_GLCM



(c) Entropy: above-GLCM, below-WT_GLCM

Figure 5 Investigation of WT effect by comparison of correlation distribution between textural measurements in undamaged areas obtained from WT and WT_GLCM method.

As shown in Fig 5, WT_GLCM method obtains more distinguishable correlation distribution for undamaged areas. It is the same to the damaged areas. This means that damaged areas and undamaged areas tend to have less common correlation values which lead inaccurate results. Thus, wavelet transformation helps to exploit textural properties.

After WT-GLCM, classification process is performed to obtain the damage map based on window-based neighborhood correlation. At this time, window size is also an important factor to affect detection accuracy. Fig 6 shows the damage detection map after classification using Mahalanobis distance measure.

(a) (b) (c)

Fig. 6 Automatic damage detection result : (a) pre-earthquake test image (b) post-earthquake test image (c) detection result: damaged area is black

IV. CONCLUSIONS

It this study, a window-based damage detection method is proposed based on the difference in textural characteristics between bi-temporal data in damaged and undamaged areas. Since remotely sensed data provide valuable information regarding land cover at the data acquisition time, they enable automatic damage detection and its mapping for natural disaster monitoring. The result is very important and useful for efficient emergency response and recovery works after event such as earthquake and flood.

It was tested that high-resolution (~0.6 m) satellite images are efficiently utilized to detect damages after earthquake. The damage detection after earthquake can be accomplished by comparing the window-based correlation comparison in textural values between two images. The correlation analysis provides the method to distinguish damaged areas since the correlation coefficient in textural measurement between pre-event and post-event tends to be high in unchanged areas and low in changed areas. Wavelet transformation helps to exploit textural properties and thus leads better damage detection solution combined with statistical analysis, GLCM method.

There are some errors sources affected the analyzed results such as inaccurate co-registration between two images, selection of parameters in texture analysis, window-size, and noisy information existent in mages. These factors could be selected differently in the experiment to see their effect. As a pre-process before doing experiment, removing noisy information such as shadows and normal urban development is also very helpful to increase the detection accuracy.

Acknowledgements

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