FUSION OF GIS DATA AND HIGH-RESOLUTION SATELLITE IMAGERY FOR POST-EARTHQUAKE BUILDING DAMAGE ASSESSMENT

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Theme

Methods and software tools for real-time data collection, processing and information extraction for disaster monitoring and damages assessment.

KEY WORDS: Change detection, Classification, Ouickbird, Damage Assessment, GIS, Temporal, High-Resolution Imagery

Abstract

Earthquake is one of the inevitable natural hazards that cause lots of damages and problems to the economy, environment and the whole life of people. Therefore, it is necessary to use all available knowledge and technologies for saving people and their assets through an efficient disaster management. Recent improvements in spatial resolution of commercial satellite imagery make it possible to apply very high-resolution satellite data for assessing structural damage in the aftermath of humanitarian crises.

However, in practice most of the processes for damage assessment are manual operations like on-screen change detection that are time consuming and expert dependent. The focus of this study was to thoroughly exploit the capability of very high-resolution (VHR) satellite imagery such as QuickBird for disaster response and relief phase. An efficient automated methodology that detects damage was implemented to derive the rich information available from VHR satellite imagery such as texture features. In this paper, we compare efficiency of each texture feature in classification accuracy for collapse and non-collapse buildings.

The potential of the proposed methodology evaluated by using the buildings layers of pre-event 1:2000 scale digital map of the city of Bam in Iran and a pan-sharpen QuickBird post-event satellite image of the Bam, acquired 8 days after December 26th 2003 earthquake.

1- Introduction

For decades, remote sensing techniques have been important in grasping damage information caused by earthquakes. Medium resolution satellite data like SPOT, Landsat (Eguchi et al. 2003; Estrada et al. 2001)[1],[2] or ERS (Matsuoka and Yamazaki 2004)[3] is mainly used to identify the extent of the damage. Damaged buildings can be detected using aerial photographs (Mitomi et al. 2000)[4]. Recently, very high-resolution (VHR) imagery from commercial satellites such as Ikonos and QuickBird, which can be rapidly acquired, is becoming more powerful and is providing information on natural and/or man-made disasters in the early stages of their unfolding. Both visual interpretation and automated analysis are currently used to detect damaged buildings,

but the latter has yet to be reliably implemented. The conventional method for detecting damage caused by an earthquake is to compare pre- and post-event images. This approach has also been developed for VHR data. For example, a new overlay method between pre- and post-event images was based on artificial neural networks (Kosugi et al. 2000)[5]. However, it is unrealistic to obtain images of the stricken areas before a disaster, and archived data with clear and suitable images is limited. Therefore, this paper addresses an automated detection method that uses only post-event images and before vector GIS map. Finally, by using spectral and features information the post-event image has been classified.
Classification is the most common method of extracting information from remotely sensed data. In conventional classification methods only spectral data are used. High resolution images have more spatial information but have not got a high spectral resolution, so using the conventional classification methods seems to be ineffective. Spatial information, which is a reach source of useful information especially in high resolution images, can be used to improve the classification accuracy. Texture quantization is an effective approach for utilization of the spatial information. There is no clear definition for image texture, but we can describe how the image texture looks e.g. fine, coarse, smooth or irregular, homogeneous and so forth by introducing Weighted Mean, Variance, ASM, Entropy features then we compare the accuracy of maximum likelihood classification by four above features.[6]

2- Texture Features

2-1 First Order Statistical Features

If (I) is the random variable representing the gray levels in the region of interest, the first order histogram P (I) is defined as[1] :

$$P(I) = \frac{number\ \ of\ \ pixel\ \ \ with\ \ \ gray\ \ level\ \ I}{Total\ \ number\ \ of\ \ Pixels}$$

Now two different features can be generated by using the following equations:

2-1-1 Weighted Mean

$$\text{Weighted Mean} = \sum_{I=0}^{Ng-1} IP(I)$$

Ng = number of gray levels

2-1-2 Variance

$$\text{Var} = \sum_{I=0}^{Ng-1} P(I)(I - WeightedMean)^2$$

2-2 Gray level Co-Occurrence Based Features

Haralick et.al[7] proposed this method to extract texture information from digital images. First Gray level co-occurrence matrix (GLCM) is produced and then several texture measures are computed from it. GLCM is a matrix that contains the number of each gray level pairs that are located at distance d and direction θ from each other. This matrix could be defined for different distances, angles and as well as for different lags.

$$GLCM_{d_i,d_j} = \frac{1}{R}\begin{bmatrix} \eta(0,0) & \eta(0,1) & . & . & \eta(0,N_{g-1}) \\ \eta(1,0) & \eta(1,1) & . & . & . \\ . & . & . & \eta(i,j) & . \\ . & . & . & . & . \\ \eta(N_{g-1},0) & . & . & . & \eta(N_{g-1},N_{g-1}) \end{bmatrix}$$

$\eta(i,j)$ #Pixel Pairs in lag (d_1, d_2) through

N_g : Number of Gray Levels

R : Total Number of Possible Pairs

In this research, following features have been generarted from the GLCM matrix :

2-2-1 Angular Second Moment (ASM)

$$ASM = \sum_{i=0}^{N_{g-1}} \sum_{j=0}^{N_{g-1}} \left(P(i,j)\right)^2$$

where P(i,j)=GLCM(i,j)

It is a measure of image smoothness. It outputs higher values when P(i,j) is concentrated in a few places in the GLCM and lower if the P(i,j) are close in value.

2-2-2 Entropy

$$Entropy = -\sum_{i=0}^{N_{g-1}} \sum_{j=0}^{N_{g-1}} P(i,j)\ln\left(P(i,j)\right)$$

It outputs higher value for a homogeneous distribution of P(i,j), and lower otherwise.

3- Case Study

In Practice, we have used before enevt building vector map and pansharped after event BAM QuickBird(Figure 1) image that polygons in vector map correspond to buildings have been cleaned so all of polygongs had been closed. Then to use of Rational Function and calculating of Rational Function's coefficients we could convert the geocoordinates of polygons to Image coordinate system. To use of polygons in image coordinate system we creat a mask image

(Figure 2) from building in order to do processing on masking area so we could reduce rate of calculating.

Figure1. Pansharped image from post-earthquake BAM QuickBird image

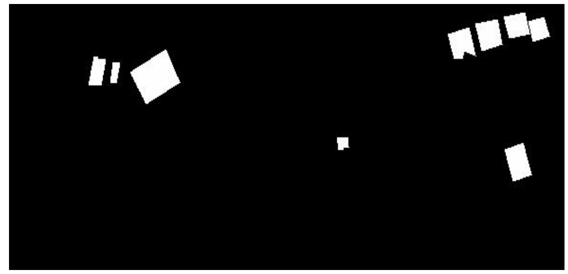

Figure2. Building Mask image

buildings have been masked in this image that some of them are Non-Collapsed and the others are entirely collapsed .We have made five images file consist of Pansharped image that four band (Red,Green,Blue,NIR) of it was masked by mask image and Weighted Mean feature image and Variance feature image and ASM feature image and Entropy feature image that all of them have got four bands and have been masked by mask image.Then each of features image accompany with Pansharped image have been classified by MaximumLikelihood classification method.For classification we define two classes for building that one is "Collapse" and other is " Non-Collapse " classes.Then we introduce 1500 point as sample data for calculating classification accuracies as can be seen in table 1.

	Total Accuracy	User's Accuracy		Producer's Accuracy	
		Collapse	Non- Collapse	Collapse	Non- Collapse
WeightedMean	83.179%	97.323%	86.559%	74.307%	90.545%
Variance	64.106%	73.764%	100.000%	78.394%	52.242%
ASM	78.146%	97.506%	79.197%	62.774%	90.909%
Entropy	78.146%	97.506%	79.197%	62.774%	90.909%

Table1. classification accuracy

To mention table 1 can be seen WeightedMean feature resulted most classification accuracy and after than ASM and Entropy features has got more classification accuracy than Variance feature so Weighted Mean feature is th best feature amount the others.
Variance feature has got 100% User's Accuracy for Non- Collapse class but it has got 52.242% Producer's Accuracy for Non- Collapse class that means only 52.242% from ground and visual samples was classified as true that it is not a desire result.
figure 3 shows classification using spectral and Weighted Mean feature for four band that red areas correspond to "Collapse" class and blue areas areas correspond to "Non-Collapse" class.

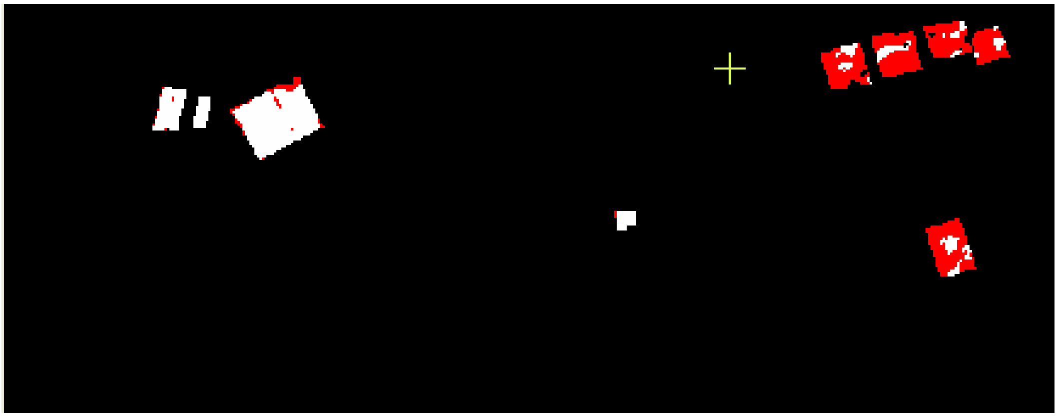

Figure3.Classification Result with using Weighted Maen feature

4.Conclusion

An automated damage detection algorithm was developed to detect damaged buildings from VHR satellite data. This method was used to analyze the 2003 Bam earthquake, and demonstrated the capability of the algorithm.We found that Weighted Mean feature has got most classification accuracy than Variance and ASM and Entropy features and we could show that collapsed and Non-Collapsed building can be detected from VHR satellite data such as QuickBird.

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