AUTOMATIC DETECTION AND CLASSIFICATION OF DAMAGED BUILDINGS, USING HIGH RESOLUTION SATELLITE IMAGERY AND VECTOR DATA

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ABSTRACT:

Receiving rapid, accurate and comprehensive knowledge about the conditions of damaged buildings after earthquake strike and other natural hazards is the basis of many related activities such as rescue, relief and reconstruction. Recently, commercial high-resolution satellite imagery such as IKONOS and QuickBird is becoming more powerful data resource for disaster management. In this paper, a method for automatic detection and classification of damaged buildings using integration of high-resolution satellite imageries and vector map is proposed. In this method, after extracting buildings position from vector map, they are located in the pre-event and post-event satellite images. By measuring and comparing different textural features for extracted buildings in both images, buildings conditions are evaluated through a Fuzzy Inference System. Overall classification accuracy of 74% and kappa coefficient of 0.63 were acquired. Results of the proposed method, indicates the capability of this method for automatic determination of damaged buildings from high-resolution satellite imageries.

1. INTRODUCTION

Receiving rapid, accurate and comprehensive knowledge about the conditions of damaged area after earthquake strike is the basis for many related activities such as rescue, relief and reconstruction. In practice, lack of information about the new conditions, may cause many problems during the process of disaster management. Prevention of natural disasters is rarely achieved with today's technology and knowledge. However, it is possible to avoid or to reduce the impacts of disasters with effective disaster management strategies. Geo-information science can provide concrete support for disaster management activities in terms of efficiency and speed up the data management, manipulation, analysis, output and value of better decisions (Montoya, 2002).

There are several data resources for getting information about the damaged area, such as optical and microwave satellite imagery, LIDAR, aerial photography and video imagery (Mitomi et al., 2000). Remotely sensed data can provide valuable information for disaster management studies. Using those data in post-disaster response is very useful, especially for the hard-hit and difficult-to-access areas (Vu et. al., 2006). Minimal fieldworks (increasing safety), continuous coverage area, digital processing and quantitative results, are advantages of use of remote sensing technology for post-earthquake damage assessment which are not affected by the disaster. Recently, commercial high-resolution satellite imagery such as IKONOS and QuickBird, which can acquire imageries with 4m and 2.4m spatial resolution in multispectral mode and 1m and 0.61m in panchromatic mode respectively, is becoming more powerful data resource for disaster management. Optical remote sensing images in many studies (Matsuoka, 2005; Chiroiu et al., 2002; Gusella et al., 2003; Huyck et al., 2005; Matsuoka et al., 2005; LIU et al., 2003; sumer et al, 2004; Guler et al., 2003; Shinozukaet al., 2000; Saito and Spence, 2004) were applied for damage assessment of earthquake. In the following section, the methodological approach for damage assessment using satellite imageries is described

2. METHODOLOGY OF BUILDINGS DAMAGE ASSESSMENT

Several automatic methods have been practiced in order to detect damaged buildings after an earthquake using satellite imagery. Generally, these methods can be categorized in "Image to Image" and "Map to Image" strategies.

2.1 Image to Image

The "Image to Image" strategy is based on comparison between pre-event and post-event images. In these methods, after registration of images, buildings in both images are extracted and compared with each other. Different pixel-based or object-oriented change detection algorithms are some of applied method in this strategy. These methods were used by several researches for automatic damage assessment (Olgun, 2000; Gusella et al., 2005; Matsuoka et al., 2005; LIU et al., 2003).

2.2 Map to Image

In the "Map to Image" strategy, after geo-referencing the map and the post-event image, locations of all buildings on the image is specified. Then, by extracting and computing spectral, textural and structural features for each candidate building, situation of the building is inspected. Therefore, having information about position of each building using vector map is the main advantage of this strategy. On the other hand, loss of information about the textural and spectral situation of buildings, before destruction, which can be useful for evaluation of extracted features from after image, seems to be the disadvantage of this strategy. This strategy was used in many damage assessment studies (Emre sumer et al, 2004; Yanamura et al., 2003; Guler et al., 2003).

3. PROPOSED METHOD FOR DAMAGE MAP GENERATION

In the first strategy, having pre- event spectral information about the buildings, and using vector data to specify buildings location on the image in the next strategy, are the advantages of both mentioned strategies. In this paper, a new strategy is proposed for damage map generation using high-resolution satellite imageries and vector data. Figure 1 presents the flowchart of the proposed strategy. As shown in the Figure 1, the proposed strategy utilizes vector map and both pre-event and post-event images of damaged area. In this section, main steps of the proposed method are described.

3.1 Pre-processing

To prepare data to be applied in the proposed method, pre-processing is performed. The pre-process is restricted to image enhancement algorithms such as histogram equalization and histogram matching, and geo-referencing step.

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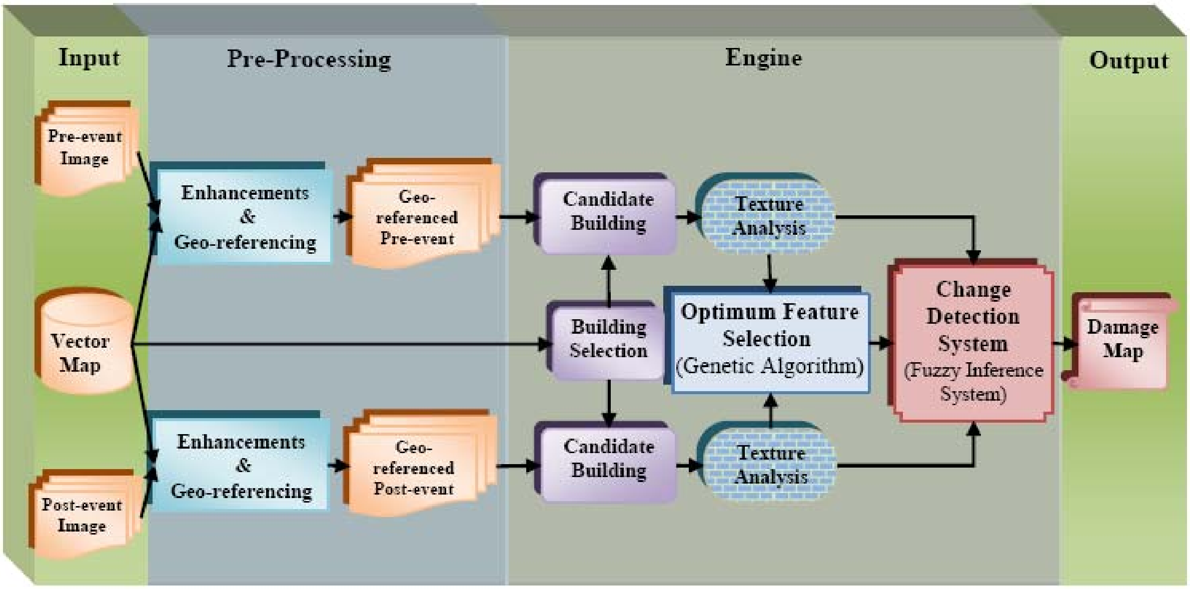


Figure 1. The flowchart of the proposed method

3.2 Engine

After pre-processing, whereas images were geo-referenced to the map, each selected building could be extracted from the images. In this research, extracted buildings are evaluated using textural features. In order to define optimum features, by using some training buildings which are known, optimum features are selected by applying Genetic Algorithm. Through inspecting the optimum features, the buildings situation using fuzzy inference system is defined. In the following, all these steps are described.

3.2.1 Texture Analysis:

In this research, 22 textural features of: 2 features of “1st Order Statistical”, 11 features of “Haralick”, 2 features of “Gabor”, 2 features of “Fractal” and 5 features of “Variogram” have been selected. Since, these features were selected in previous researches of earthquake damage assessment, they were selected.

1st Statistical Features: In texture analysis, mean and variance of gray value are used as 1st statistical textural feature (Jähne et al., 1999). In this case, the mean and standard deviation pixels gray value for candidate building are considered as 1st statistical features of extracted building.

Haralick Features: Two-dimensional co-occurrence (gray-level dependence) matrices, proposed by Haralick in 1973, are generally used in texture analysis because they are able to capture the spatial dependence of gray-level values within an image (Haralick et al., 1973). A 2D co-occurrence matrix, P, is an n x n matrix, where n is the number of gray-levels within an image. The matrix acts as an accumulator so that P[i, j] counts the number of pixel pairs having the intensities i and j. Pixel pairs are defined by a distance and direction which can be represented by a displacement vector d=(dx,dy), where dx represents the number of pixels moved along the x-axis, and dy represents the number of pixels moved along the y-axis of an image slice. So, Haralick features for extracted building area on both before and after images are measured. The formulas of these features are showed in Table 1.

Feature	*Formula*
Entropy	$-\sum_{i}^{M}\sum_{j}^{M} P[i,j]\log P[i,j]$
Energy	$\sum_{i}^{M}\sum_{j}^{M} P^{2}[i,j]$
Contrast	$\sum_{i}^{M}\sum_{j}^{M} (i-j)^{2} P[i,j]$

Homogeneity	$\sum_{i}^{M}\sum_{j}^{M}\frac{P[i,j]}{1+\lvert i-j\rvert}$
SumMean	$\frac{1}{2}\sum_{i}^{M}\sum_{j}^{M}(iP[i,j]+jP[i,j])$
Variance	$\frac{1}{2}\sum_{i}^{M}\sum_{j}^{N}((i-\mu)^2P[i,j]+(j-\mu)^2P[i,j])$
Correlation	$\sum_{i}^{M}\sum_{j}^{M}\frac{(i-\mu)(j-\mu)P[i,j]}{\sigma^2}$
Maximum Probability	$\underset{i,j}{\overset{M}{Max}}(P[i,j])$
IDM	$\sum_{i}^{M}\sum_{j}^{M}\frac{P[i,j]}{(i-j)^k}, i\neq j$
Cluster Tendency	$\sum_{i}^{M}\sum_{j}^{M}(i+j-2\mu)^k P[i,j]$

Table 1. Some texture features extracted from gray level co-occurrence matrices.

Gabor Features: For a given image I(x, y) with size P×Q, its discrete Gabor wavelet transform is given by a convolution (Tuceryan, 1998):

$$G_{mn}(x,y)=\sum_{s}\sum_{t}I(x-s,y-t)\psi^{*}_{mn}(s,t) \quad (1)$$

Where, s and t are the filter mask size variables, ψ^{*}_{mn} is the complex conjugate of ψ_{mn} and m and n specify the scale and orientation of the wavelet respectively, with m = 0, 1,…,M-1, n = 0, 1, …, N-1. Here, the mean and standard deviation of the magnitude of the transformed coefficients are used to represent the homogenous texture feature of a building.

Semivariogram Features: Semivariance calculations can be performed for texture analysis. The semivariogram is calculated from the raster images using digital numbers (DN)(Chica-olmo, 2004). Table 2 shows some extracted features from semivariogram.

Feature	*Formula*
Simple Variogram	$\gamma_k(h)=\frac{1}{2n(h)}\sum_{i=1}^{n(h)}\{DN_k(x_i)-DN_k(x_i+h)\}^2$
Madogram	$\gamma_k(h)=\frac{1}{2n(h)}\sum_{i=1}^{n(h)}\lvert DN_k(x_i)-DN_k(x_i+h)\rvert$
Radogram	$\gamma_k(h)=\frac{1}{2n(h)}\sum_{i=1}^{n(h)}\sqrt{\lvert DN_k(x_i)-DN_k(x_i+h)\rvert}$
Cross variogram	$\gamma_{jk}(h)=\frac{1}{2n(h)}\sum_{i=1}^{n(h)}\{DN_j(x_i)-DN_j(x_i+h)\}^{*}\{DN_k(x_i)-DN_k(x_i+h)\}$
Pseudo-cross variogram	$\gamma_{jk}(h)=\frac{1}{2n(h)}\sum_{i=1}^{n(h)}\{DN_j(x_i)-DN_k(x_i+h)\}^{*}\{DN_j(x_i)-DN_k(x_i+h)\}$

Table 2. Some texture features extracted from variogram

Fractal Features: Mandelbrot proposed fractal geometry and is the first one to notice its existence in the natural world (Mandelbort, 1983). The fractal dimension gives a measure of the roughness of a surface. Intuitively, the larger the fractal dimension, the rougher the texture is (Jähne et al., 1999). In this paper, the mean and standard deviation of calculated fractal dimension for a building's pixels are considering as fractal textural features for extracted building.

3.2.2 Optimum Feature Selection

Genetic Algorithm solves the problem of finding good chromosomes by manipulating the material in the chromosomes blindly without any knowledge about the type of problem they are solving. The only information they are given is an evaluation of each chromosome they produce. This evaluation is used to bias the selection of chromosomes so that those with the best evaluations tend to reproduce more often than those with bad evaluation (Goldberg, 1989). In this case, chromosomes are textural features vector that have 22 genes representative of 22 features. True value for any gene means the presence of corresponding feature in the feature vector. Evaluation function of the algorithm is overall accuracy of the maximum likelihood classification of training buildings. Thus, the fitness criterion is to maximize overall accuracy of classification. Maximum Likelihood classification is performed for each feature vector in the each iteration and resulted overall accuracy is used as GA cost function. The iteration is terminated when all chromosomes show same features vector. The final obtained features vector is selected as optimum features. Encoding of feature vector into an n-bit chromosome string is showed by Figure 2.

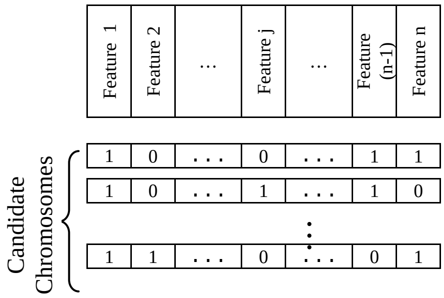


Figure 2. Encoding of feature vector into a n-bit chromosome string

3.2.3 Damage Detection System

After selecting optimum textural features, destructed buildings situations are evaluated. According to existences of ambiguity and vague in determination of buildings destruction, a Fuzzy Inference System is used. Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. Fuzzy sets, that proposed by zadeh (zadeh, 1965), and fuzzy operators are the subjects and verbs of fuzzy logic. Usually the knowledge involved in fuzzy reasoning is expressed as rules in the form:

If x is A Then y is B

Where, x and y are fuzzy variables and A and B are fuzzy values. The if-part of the rule "x is A" is called the antecedent or premise, while the then-part of the rule "y is B" is called the consequent or conclusion. Statements in the antecedent (or consequent) parts of the rules may well involve fuzzy logical connectives such as 'AND' and 'OR'.

In the proposed Fuzzy Inference System, differences between optimum textural features, extracted from pre-event and post-event images, for candidate building are considered as input linguistic variables and building labels ("Undamaged to Negligible Damaged", "Moderate Damaged", "Heavily

Damaged" and "Destructed") are assigned as output linguistic variables (Figure 3).

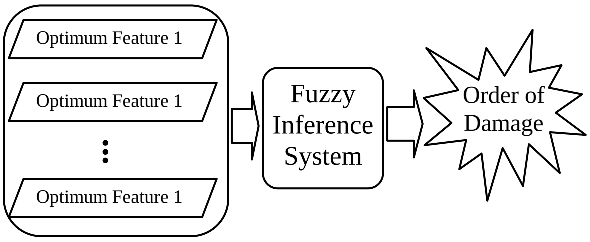


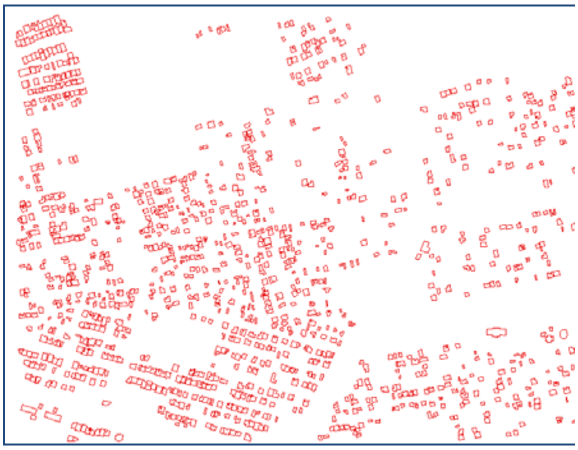
Figure 3. Damage assessment operation using fuzzy inference system

4. EXPERIMETNS AND RESULTS

The proposed method in this study is evaluated using before and after December 26th 2003 earthquake QuickBird multi-spectral images of Bam, Iran, acquired on September 30th 2003 (pre-event scene) and January 3rd 2004 (post-event scene) and relevant 1:2000 vector map of the city. From available images, a 1900*2500 pixels area was selected as test area. Figure 4 shows the data set after pre-processing step.

(a)

(b)

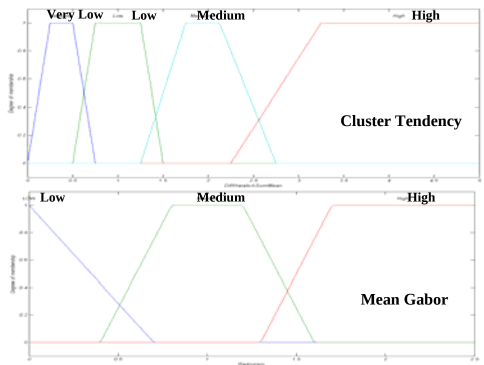


(c)

Figure 4. Data set. (a) pre-event Image after pre-processing (b) post-event Image after pre-processing (c)extracted building layer form vector map

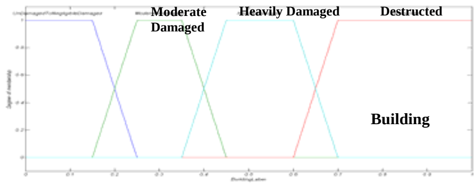
For the purpose of optimum feature selection, the GA is applied. In this research, after 8 iterations of applied GA "mean" form 1st statistical, "mean" from Gabor, "mean" from fractal, "Radogram" from semi-variogram, "Entropy", "Homogeneity", "Sum Mean", "Cluster Tendency" and "variance" from Haralick features are selected as optimum features.

After extracting the buildings layer from vector map, 1137 buildings were defined in the test area. 4 buildings were removed from 1137 list of buildings because of their negligible size. Other 1133 buildings were classified using a Fuzzy Inference System into "Undamaged to Negligible Damaged", "Moderate Damaged", "Heavily Damaged" and "Destructed" classes. The membership functions for the variable of the fuzzy system based on the some buildings, which they situated by expert operator, are defined. Two input variables and the only output variable is depicted in Figure 5. Also, Table 3 shows some sample rules in the used Fuzzy system.



Negligible Damaged

(a)



(b)

Figure 5. some membership functions (a) membership function of input variables (b) membership function of output variable

If (SpectralMean is Low) and (GaborMean is Low) and (FractalMean is Low) and (HaralickEntropy is Low) and (HaralickVariance is Low) and (HaralickClusterTendency is Low) and (HaralickSumMean is Low) and (HaralickHomogenity is Low) then (BuildingLabel is UnDamaged)
If (SpectralMean is High) and (GaborMean is High) and (FractalMean is High) and (HaralickEntropy is High) and (HaralickVariance is High) and (HaralickClusterTendency is High) and (HaralickSumMean is High) and (HaralickHomogenity is High) then (BuildingLabel is Destruction)

Table 3. some sample rule in Fuzzy Inference system

Final damage map generated using this method is depicted in figure 6 and number of buildings assigned to each of these classes is showed in Table4.

	Number of Buildings	Percentage
Undamaged to Negligible Damaged	**128**	**11.30**
Moderate Damaged	**276**	**24.36**
Heavily Damaged	**349**	**30.80**
Destructed	**380**	**33.54**
Summation	**1133**	**100**

Table 4. Number of buildings according to each class

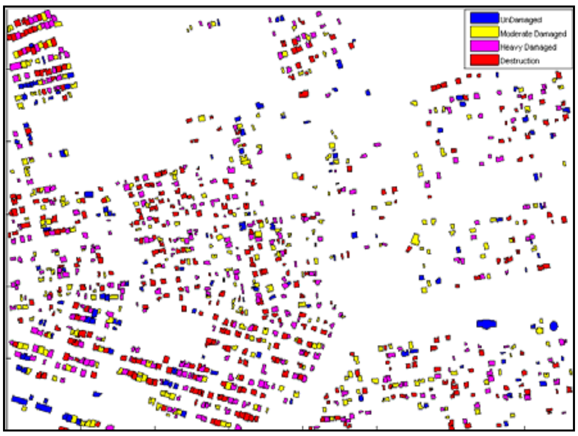


Figure 6. Resulted damage map for test area

Confusion matrix was calculated using 100 randomly selected buildings as reference dataset which were situated by visual observations. Overall accuracy of 74% and kappa coefficient of 0.63 were acquired for our classification. Resulted confusion matrix is presented in Table 6. Also, resulted user accuracy, producer accuracy and overall accuracy is illustrated in Figure 7.

		Proposed Method					
	Confusion	Class1	Class 2	Class 3	Class 4	OE	PA
Reference Data	Class 1	9	1	0	0	0.1	0.9
	Class 2	3	12	4	1	0.42	0.58
	Class 3	0	7	27	1	0.23	0.77
	Class 4	0	1	8	26	0.25	0.75
	CE	0.25	0.43	0.31	0.07		
	UA	0.75	0.57	0.69	0.93		

Table 5. confusion matrix. (Class1)Negligible to Undamaged. (Class2)Moderate Dameged. (Class 3)Heavily Damaged. (Class4) Destructed.

The results of the confusion matrix, indicates the good capability of this method to separate “Undamaged to Negligible Damaged” and “Destructed” classes from other classes.

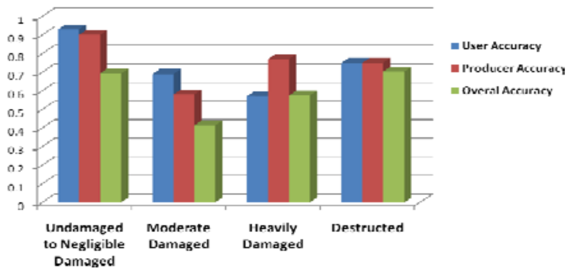


Figure 7. Resulted user accuracy, producer accuracy and overall accuracy

5. CONCLUSION AND REMARKS

In this study, we presented a new method for generating damage map through texture analysis on pre-vent and post-event high resolution satellite imageries. In the test area, a total of 1133 buildings were analyzed to measure their conditions. The results are quite encouraging. The overall accuracy and kappa coefficient of 74.4% and 0.63 were computed.

Obtained results prove the ability of high resolution satellite imageries in assessment of earthquake destruction.

Using Genetic Algorithm in optimum feature selection and Fuzzy Inference System to handle existing ambiguity in decision making is regarded as main capabilities of this method.

Considering importance of data fusion, it’s proposed to use all available data sources to make better decisions. Besides, because of capability of textural features in damage assessment, it’s recommended to consider other features to be used.

REFERENCES

Chica-Olmo M. and Abarca-Hernández. F., 2004. Variogram Derived Image Texture for Classifying Remotely Sensed Images., Remote Sensing Image Analysis: Including the Spatial Domain, 93–111.

Chiroiu, L., Andre, G., Guillande, R., and Bahoken, F., 2002. Earthquake Damage Assessment using High Resolution Satellite Imagery, Proceedings of the 7th National US Conference on Earthquake Engineering, Boston.

Earthquake Damage Assessment for Bam, Iran, Using Very High Resolution Satellite Imagery, 2nd International Workshop on Remote Sensing for Post-Disaster Response, University of Bologna

Goldberg, D.E., 1989. Genetic Algorithms in Search, Optimization & Machine Learning, Addison-Wesley Longman.

Guler, M.A., Turker, M., 2003., Detection of the Earthquake Damaged Buildings from Post-Event Aerial Photographs Using Perceptual Grouping., ISPRS Conference, Commission III, WG III/4

Gusella, L., Bitelli, G., Mognol, A., Huyck, C.K., Adams, B.J., 2004, Object Oriented Approuch to Post-Earthquake Damage Assessment for Bam, Iran, Using Very High Resolution Satellite Imagery, 2nd International Workshop on Remote Sensing for Post-Disaster Response, University of Bologna

Gusella, L., Huyck, C.K., Adams, B.J., Cho, S., Chung, H., 2005. Damage Assessment with Very-High Resolution Optical Imagery Following the December 26, 2003 Bam, Iran Earthquake , University of Bologna

Haralick, R.M., Shanmugam, K., Dinstein, I., 1973. Textural features for image classification., IEEE Trans. Systems, Man Cybernet., 3, 610–621.

Jähne, B. (et al., eds.)., 1999. Handbook on Computer Vision and Applications,, volume 2., pp 239-274., Academic Press, Boston, USA.

LIU Jia-hang, SHAN Xin-jian, YIN Jing-yuan., 2003. Automatic recognition of damaged town buildings caused by earthquake using remote sensing information: Taking the 2001 Bhuj, India, earthquake and the 1976 Tangshan, China, earthquake as examples., ACTA SEISMOLOGICA SINICA, Vol.17 No.6 (686~696)

Mandelbrot, B. B., 1983. The Fractal Geometry of Nature, Freeman, San Francisco.

MATSUOKA, M. and VU T.T. and YAMAZAKI, F., 2005. Automatic Damage Detection And Visualization Using High resolution Satellite data for Post-Disaster Assessment.
Mitomi, H., Yamazaki, F., & Matsuoka, M., 2000. Automated Detection of Building Damage due to Recent Earthquakes Using Aerial Television Images.

Montoya, L., 2002. Gis and Remote Sensing in Urban Disaster Management. Paper presented at the 5th AGILE Conference on Geographic Information Science, Palma.

Olgun, E., 2000. Izmit (Turkey) Earthquake, August 17,1999 and the Application of Change Detection Techniques for Damage Assessment Using Spot4 Satellite Images.

Saito, K and Spence, R., 2004. Using High-resolution Satellite Images for Post Earthquake Building Damage Assessment: A Study Following the 26.1.01 Gujurat Earthquake, Earthquake Spectra.

Shinozuka, M., Lee, G., Chen, Z and Yen, C., 2000. Applications of Remote Sensing, The Chi-Chi Taiwan Earthquake of September 21, 1999: Reconnaissance Report, MCEER-00-0003, Multidisciplinary Center for Earthquake Engineering Research, University at Buffalo, pp. 95-100.

SÜmer, E., & TÜrker, M., 2004. Earthquake Damage Detection Using Watershed Segmentation and Intensity-Gradient Orientation Approaches., Master Thesis submitted to the Graduate School of Natural and Applied Sciences., Middle East Technical.

Zadeh, L.A., (1965)., Fuzzy Sets., Information and Control