An attempt of using straight-line information for building damage detection based only on post-earthquake optical imagery

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Abstract: It is important to grasp damage information in stricken areas after an earthquake in order to perform quick rescue and recovery activities. Recent research into remote sensing techniques has shown significant ability to generate quality damage information. The methods based on only post-earthquake data are widely researched especially because there are no pre-earthquake reference data in many cities of the world. This paper addresses a method for detection of damaged buildings using only post-event satellite imagery so that scientists and researchers can take advantage of the ability of helicopters and airplanes to fly over the damage faster. Statistical information of line segments extracted from post-event satellite imagery, such as mean length (ML) and weighted tilt angel standard deviation (WTASD), are used for discriminating the damaged and undamaged buildings.

1. Introduction

Earthquakes, such as the 2008 Wenchuan earthquake in China, 2010 earthquake in Haiti and 2011 Tohoku earthquake in Japan, have caused huge casualties and economic lose all over the world in recent years. Although earthquakes are inevitable, humans can change the way they respond to them. Fortunately, remote sensing techniques both by spaceborne and airborne sensors can make great contribution especially in the response and recovery phases. Earthquake-induced building damage is one of the most critical destructions in cities. The amount of collapsed buildings, the damage grade of the affected area, and the damage type of each building are essential information to decide how to rescue and reconstruct in the disaster areas [1]. High resolution remote sensing is an effective tool for disaster monitoring and building damage detection because of its characteristics of low cost, large coverage and fast data acquisition capability.

Very high resolution (VHR) remote sensing imagery with detailed texture and context information makes it possible to detect building damage based on only post-earthquake data. Therefore, scholars all over the world paid attention to this subject and carried out much fruitful work. After the post-earthquake optical image being conducted by Sobel operator, edge direction was calculated pixel by pixel and used to detect damaged area [2]. Mitomi et al. (2001) proposed a method of detecting damaged areas based on edge intensity, variance, and the ratio of predominant direction of edge intensity [3]. Vu et al. (2005) followed the previous work and applied the angular second moment and entropy of edge intensity to detect areas with collapsed buildings [4]. Huyck et al. (2005) introduced
an edge dissimilarity algorithm to quantify the extent of building damage [5]. In addition, textural features calculated based on gray level co-occurrence matrix (GLCM) were commonly used in the research of [6-10]. Reviewing the above mentioned studies, the differences of spectra, texture, edge, spatial relationship, structure, shape, and shadow between undamaged and damaged buildings in post-event data are used for building damage detection. We can find that only the information of no more than eight neighbor pixels is considered for each pixel in these methods, and the information of the pixels a litter further from each pixel has not been fully utilized. This paper presents a method for the detection of damaged buildings using statistic information of line segments extracted from only post-event high resolution satellite imagery.

2. Data and methodology

2.1 Basic assumption

The satellite remote sensing images of Port-au-Prince, which were acquired on 25th January 2010 after the Haiti earthquake, are supplied by Google Earth. An area of 1758*1137 pixels from the image is chosen for experiments (see Figure 1).

**Figure 1.** Image segment of Port-au-Prince after the Haiti earthquake (from Google Earth)

As shown in Figure 1, the spectral and grayscale difference among various building roofs are so huge that only using color information for detection of damaged buildings may not lead to good results. Most of the intact buildings in Port-au-Prince city are rectangular with straight edges. We can see that, in the area with collapsed buildings, the building edges are broken into many small pieces which scattered randomly, as in the areas with un-collapsed buildings, the edges are intact and uniform. Thus our method is based on the assumption that the areas with collapsed buildings have a lot of short edges in random directions. Straight lines are very important intermediate level symbol in image analysis. Statistic information of straight line segments is used for detecting the areas with damaged buildings in this method. The first is the ML of straight line segments within a certain image window. The second is the WTASD of the detected straight lines.

2.2 Feature extraction

2.2.1. Mean length. Firstly, a canny edge detector is applied to the lightness image to get the edge information [12]. Secondly, the extracted edges are fitted to straight line segments using Douglas-Peucker algorithm. The two end points of each straight line segment are recorded. Thirdly, the whole image is divided into a certain number of image windows. For each image window, the ML
of the straight line segments, of which no less than one end point is determined within the image window, is calculated using equation (1).

\[
\text{Mean Length} = \frac{1}{n} \sum_{i=1}^{n} \sqrt{(x_{2i} - x_{1i})^2 + (y_{2i} - y_{1i})^2}
\]  

(1)

\(n\) is the number of the straight-line segments in the detection window, \(x_{1i}, x_{2i}, y_{1i}, y_{2i}\) are the coordinates of the end points of each straight-line segments.

2.2.2. Weighted tilt angle standard deviation. The orientation histogram is introduced in Lowe’s Scale Invariant Feature Transformation (SIFT) approach [13]. Within a detection window, the orientation of each straight line segment, namely tilt angle of the straight line, is calculated in term of equation (2). Each straight line segment calculates a weighted vote for an orientation histogram channel. The ten orientation bins are evenly spaced over \(0 - 180^\circ\). The vote is weighted by the length of each straight line segment.

\[
\text{orientation} = \arctan\left(\frac{y_2 - y_1}{x_2 - x_1}\right)
\]  

(2)

2.3 Determination of the areas with damaged buildings

First, the threshold values of the two features are determined by training samples selected manually. Then the detection window area having two features within the range of the two threshold values are determined as the area with damaged buildings.

3. Experiments and analysis

To investigate the discriminatory power of the statistical features, ML and WTASD, four areas have been chosen for experiments (see Figure 2).

![Figure 2. Image segments from Figure 1; (a), (c) are the areas of damaged buildings; (b), (d) are the areas of undamaged buildings.](image)

Seen from Figure 2, using Douglas-Peucker linear fitting algorithm, when the minimum length of the extracted straight lines is set as 10 pixels and the fitting error is 4 pixels, 22, 13, 19 and 11 straight...
lines are extracted from the image segment a, b, c and d respectively. Assumed that the range of the tilt angle of the extracted straight lines is $[0, 180^\circ]$ and the number of orientation bins is ten, the distributions of the length and tilt angle are shown in Figure 3.

![Figure 3](image)

**Figure 3.** The distributions of the length and the tilt angle of the straight line segments in image windows in Figure 2. For each image window, X-axis refers to the length (above) and the orientation (below); Y-axis refers to the number.

Statistical features, such as the ML and WTASD, are calculated for each segment. How to calculate them has been introduced in section 2. The results are shown in Table 1.

**Table 1.** The ML and WTASD of the straight lines within the image segments a, b, c and d

|        | a   | b   | c   | d   |
|--------|-----|-----|-----|-----|
| ML (pixel) | 16.2 | 33.5 | 16.1 | 42.6 |
| WTASD (radian) | 0.18 | 0.57 | 0.19 | 1.1 |

These four areas with different damage grades are all chosen from the city of Port-au-prince. Therefore, buildings within these areas have similar features like size and shape. Seen from Table 1, image segment d has the longest ML, followed by b, a and c. The main reason is that an edge may be broken into two or more shorter ones with different tilt angles when the building is collapsed. This relationship can be used to discriminate between damaged and undamaged areas. However the
quantitative relationship between the ML and the damage grade needs to be figured out by huge samples in future work. On the other hand, the segments of b and d have bigger WTASD than a and c. When the building is collapsed, an edge may be broken into many small ones and their directions are random, in other words, the directions of the straight lines extracted from the area with collapsed buildings are random. As a result, the WTASD of the area with more collapsed buildings would be smaller. Therefore the threshold of WTASD can be used for discriminating the damaged and undamaged areas.

4. Conclusion
This paper just concentrates on the extraction and performance of the proposed features. The information of straight lines extracted from the building area can be used to detect the collapsed buildings based on only post-earthquake image. It’s evident from the discussion that straight line is a very promising feature for earthquake-induced building damage detection in cities, especially in the big cities with rectangular buildings. The ML and WTASD are demonstrated in this paper. Detection window with combined the ML and WTASD will be fed to a conventional linear SVM for the automatic detection of damaged buildings in the future. If the pre-earthquake image data are available, comparing the statistical features of the straight line segments extracted from the pre-earthquake image and that from the post-earthquake image in the same geographical position may lead more reliable results as compared to using only post-earthquake image data. Using only post-event data is difficult to ascertain the exact damage grade of each building, but still meet the requirements of rapid damage assessment in the emergency response period.

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