Detecting collapsed buildings from image data for estimation of disaster debris

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Abstract. In the event of a massive earthquake, it is difficult to assess the situation in affected areas because access to these areas is usually blocked off. Tsunamis, in particular, create a large amount of debris and block many access paths. It is necessary to estimate the amount of disaster debris as early as possible in order to begin restoration in affected areas. This data helps to determine the required amount of temporary storage and arrange proper transportation. We propose a system that detects collapsed buildings after a disaster by using three aerial photographs. We verify the accuracy of the proposed method and discuss how detecting collapsed buildings aids in estimating total disaster debris.

1 Introduction

The Great East Japan Earthquake, which occurred on March 11, 2011 in Japan, caused enormous damage. The earthquake occurred with a Tsunami, destroying many houses and access paths. Additionally, the Tsunami left large amounts of debris in the affected areas. Media outlets all over the world reported this crisis. According to a report on the day after the earthquake, the area of collapsed buildings caused by the Tsunami was approximately 150 square kilometers. The collapsed buildings included infrastructure facilities such as stations. As a result, access to the affected areas was blocked by debris, flooding, and land subsidence. This forced the use of helicopters for damage surveying and rescue work.

One important aspect of restoration is assessing a situation to enable the removal and disposal of disaster debris. For disaster debris disposal, it is necessary to estimate the amount of disaster debris as early as possible. Furthermore, determining the required amount of temporary storage and arranging transportation is also essential. Both of these tasks also require an estimate of disaster debris. This is why estimating the amount of disaster debris is an essential task for restoration of the affected areas. However, little information is typically available from the affected areas immediately following a disaster. We focus on the use of aerial photographs, which can be taken immediately after a disaster, to accomplish debris estimation.

We propose a system that detects collapsed buildings after a disaster by using aerial photographs. This data is used to estimate the total amount of disaster debris. To detect collapsed buildings using aerial photographs, we create a classifier based on characteristics such as the number of straight lines in the images. We then apply the proposed method to a real aerial photograph taken after a disaster. The aerial photographs used were taken in the affected areas at the time of the Great East Japan Earthquake.
2 Related works
Disasters generate large amounts of debris. Some researchers have examined debris management plans and methods from real disasters such as Hurricane Katrina or the Great East Japan Earthquake. Some frameworks for methods to restore the affected areas have also been proposed. Luther et al. provided an overview of the types and amount of debris generated by Hurricane Katrina, as well as the unique complicating factors involved. Brown et al. examined various aspects of disaster debris management, such as debris management goals, prioritization and timing, environmental impact, economics, social factors, organizational and coordination structures, legislative issues, and financial aspects or funding mechanisms. Nojima et al. described a framework for estimating damage using various dimensions. The first dimension uses a combination of a fragility function and seismic information. The second dimension is data from affected areas, gathered using remote sensing methods. The third dimension is information obtained through audits of the disaster area. This final dimension is typically the most reliable. However, capturing this information takes large amount of time and manpower. Therefore, it is difficult to use this dimension immediately after a disaster. We focus on the second dimension because it is easier to obtain than the third dimension, and more specific than the first dimension.

Some researchers have focused on the estimation of the amount of disaster debris. They also used the previously described secondary information. Hirayama et al. proposed a system that estimates the amount of disaster debris in Tsunami-inundated areas. Mitomi et al. analyzed debris characteristics in aerial photographs to detect heaps of debris. Some other studies that detect collapsed buildings have been conducted. Matsuoka et al. built a system that detects building damage in areas affected by an earthquake using satellite SAR intensity images. Urabe et al. analyzed road blockages after earthquakes in mountainous areas. They detected damaged areas by comparing two images with a digital elevation model. Sakurada et al. proposed a method for detecting temporal changes in three-dimensional structures from multi-view images captured at different times.

3 Detecting collapsed buildings
We target the detection of collapsed buildings in this paper. If collapsed buildings can be detected, the amount of disaster debris can be estimated. We focus on aerial photographs and map data to detect collapsed buildings. This is because they can be easily obtained at the time of a disaster. They are both taken in the areas affected by the disaster.

Image data, including aerial photographs, has standard image characteristics. We can use these to detect collapsed buildings. We focus on regions of the image likely to contain a building. A building that collapses after a disaster should create debris. On the other hand, a building that has not collapsed should appear as it did before the disaster. Our proposed processing method follows the process below:
1) Acquire image data.
2) Focus on region of image likely to contain a building.
3) Extract features from focus region.
4) Classify building as collapsed or not collapsed.
We describe the specific features and how extract them below.

3.1 Focus on Image Region
A building that is captured in an aerial photograph and a building found on a map are in the same position in both images. We now discuss a method that uses this fact to focus on a particular image region.

Initially, the system focuses on a building on the map. Next, the system trims the aerial photograph to encompass the same area defined by the map coordinates. As a general rule, one focus region contains one building. If it is determined that the target building is damaged, the affected area is added to the size of the target building, which is obtained from the map data. Figure 1 shows an example of the process.
3.2 Feature Extraction

It is necessary to analyze the aerial photographs and quantify which features indicate the presence of damage. To classify collapsed buildings using aerial photographs, we use extracted image features.

We focus on the roofs of houses in this paper. Typically, if a house is drawn on a map, the roof of the house is captured in an aerial photograph. However, if the target house has collapsed, the roof will appear differently, or be missing entirely in the aerial photograph. Therefore, the condition of roofs is a feature that can classify damage. The actual process is shown below.

3.2.1 Convert color image into grayscale. An aerial photograph is a color image. The first step is to convert $RGB$ color information into luminance.

Equation (1) is the conversion equation. The equation is applied to all pixels. The result is a color aerial photograph converted into a grayscale.

$$Y = 0.299r + 0.587g + 0.114b$$

Where $Y$ represents the 0-255 luminance value of each converted pixel. $r$, $g$, and $b$ are the $RGB$ values of each pixel before conversion. Figure 2 displays an example conversion result.

Figure 2. Conversion of color image into grayscale image.

3.2.2 Creating a differential image: Sobel Filter. By applying a differential filter, we can extract the portion of a grayscale image where brightness changes rapidly. This allows the detection of roof edges. For this research, we chose the widely used Sobel filter.

The Sobel filter is defined by equations (2) and (3).  

$$g(x, y) = (-1)f(x - 1, y - 1) + (-2)f(x, y - 1) + (-1)f(x + 1, y - 1) + f(x - 1, y + 1) + 2f(x, y + 1) + f(x + 1, y + 1)$$

$$g(x, y) = (-1)f(x - 1, y - 1) + f(x + 1, y - 1) + (-2)f(x - 1, y) + 2f(x + 1, y) + (-1)f(x - 1, y + 1) + f(x + 1, y + 1)$$

Where $g(x, y)$ is a pixel value in the resulting image, $f(x, y)$ is a pixel value in the grayscale image, and $x, y$ is the pixel coordinate. Figure 3 shows an example of a differential image.
Figure 3. Conversion from grayscale into differential image.

A differential image is a grayscale image, meaning it is multi-valued. To carry out detection of line segments, it must be binarized using an automatic threshold selection method on the obtained image. Specifically, we search for a threshold value $t$ that maximizes the following equation (4) for a luminance histogram.

$$ t = \max\{\omega_1 \omega_2 (m_1 - m_2)^2\} $$

(4)

Where $t$ is a threshold used to divide two classes, $\omega_l$ is the average of a class, and $m_l$ is the divergence of a class.

3.2.3 Detecting Straight Lines. If a house has not collapsed, a differential image will contain defined roof edges. Typically, roof edges are straight lines, so it is necessary to detect straight lines in a differential image.

The Hough transformation is used to detect straight lines. We apply the widely used $\theta\rho$-Hough transformation to a differential image. If a house has not collapsed, the straight lines of a roof can be found by applying the Hough transformation. On the other hand, if a house has collapsed, straight lines will not be found. Furthermore, sand and debris will be present in their place.

The Hough transform is a method of converting XY-coordinates into polar coordinates. It is applied to all original pixel values using equation (5).

$$ \rho = x \cos \theta + y \sin \theta $$

(5)

Where $x, y$ is a coordinate in an image. By applying equation (5), coordinates become a relationship between $\rho$ and $\theta$. As shown in Figure 4(a), similar processing is applied to all other coordinates. If the points are arranged in a straight line, the curves will intersect at one point as shown in Figure 4(b). To find straight lines, we look for many overlapping points in the polar plane. Then the point is converted back into a straight line in the XY plane. In this research, we determined a threshold parameter using equation (6). Coefficients for this equation were determined through preliminary experiments.

$$ t = 0.0085S + 16.75 $$

(6)

Figure 4. The principle of the $\rho\theta$-Hough transformation.

Figure 5 shows an example of line detection. Red lines are the results of the $\rho\theta$-Hough transformation.
superimposed over the original image.

Figure 5. The results of the $\rho\theta$-Hough transformation.

4 Estimating disaster debris
We used equation (7) for estimating disaster debris.

$$W_D = \sum_{i=1} C_i N_i$$  \hspace{1cm} (7)

Where $W_D$ is the amount of debris. $C_i$ is a basic unit for disasters that is defined by disaster types and building structures (e.g. Was collapse caused by fire or earthquake? Is a structure rebar or wooden?). $N_i$ represents the number of collapsed buildings. It can be used to indicate the physical area of collapsed buildings.

If a building is classified as “collapsed,” the building area is added to the total damage area. At this time, building areas are converted into physical areas. We defined the basic unit of disaster using a wooden building collapse. The unit is debris created per square meter, $0.62$ [ton/m$^2$].

5 Experiment and evaluation
In this section, we describe the experimental results and evaluate the difference between real damage and our prediction. We performed the following experiment to verify the proposed method. Our proposed method detects collapsed buildings from image features. It then calculates the collapse area and the amount of disaster debris left by the building. We compare the prediction results with the actual damage for each building to evaluate the proposed method.

5.1 Aerial Photograph and Map Data
A set of images is prepared for the experiment. The images are an aerial photograph taken after a disaster and a map of the affected areas. Information on the location and area of each building can be obtained from the map. Test images are required to satisfy the following conditions: collapsed building percentage in aerial photographs is nearly fifty percent, a map corresponding to the buildings in the aerial photographs exists, and real damage information is known.

We prepared images that satisfied all conditions. In this experiment, we used images of Minamisanriku Town, Rikuzentakata City, and Kamaishi City, in Japan. The images are all from areas affected by the Great East Japan earthquake.

Images scale is either 1:2500 or 1:4500. Pixel density is 24 dpi. The photographs come from the Geospatial Information Authority of Japan. They are shown in figure 6 below.

Figure 6. Example aerial photographs of affected areas.

We use a Geographic Information System (GIS) for map data. The map data is publicly available from the Great East Japan Earthquake Reconstruction Support Research Archive. The available map information is the position of buildings, area of each building, and a classification of the damage. We use
only the position and area of buildings.

5.2 Damage Data from the Actual Disaster
To evaluate the validity of the experimental results, we gathered the actual damage data from the Great East Japan Earthquake Reconstruction Support Research Archive for comparison. This data was created through a huge investment of time and manpower. Figure 7 displays an example of this data. The image has been blurred to protect the privacy of the victims. By using the color data, we can verify the location, size, and damage level of every building.

![Damage Data Image]

**Figure 7.** Actual damage data from the Great East Japan Earthquake Reconstruction Support Research Archive.

Red indicates a collapsed building dragged away by the tsunami, pink indicates a collapsed house in place. We defined all collapsed buildings using these two colors. The colors used for buildings that have not completely collapsed are yellow, blue, and green. Yellow indicates half-collapsed, and blue indicates partially-collapsed. According to the Japanese Ministry of Internal Affairs and Communications, half-collapsed and partially-collapsed are defined as buildings that can be restored by repairs. Finally, green indicates buildings that were not damaged.

5.3 Evaluation of Experimental Results
We use three metrics to evaluate experimental results: percentage of correct answers, precision, and recall. Figure 8 shows the legend, and the correct answers are $A_r$ and $A_b$.

![Legend Image]

**Figure 8.** Legend for experiment results.

$A_r$ is the number of correct “collapsed” predictions. $A_b$ is the number of correct “non-collapsed” predictions. In this paper, we define the percentage of correct answers as the sum of $A_b$ and $A_r$ over total predictions.

The next metric used to measure the effectiveness of the proposed method is precision. Precision P is defined by equation (8).

$$P = A_r / (A_r + A_b)$$  

(8)

This is the fraction of "collapsed" predictions over the actual number of collapses. Precision is used
in conjunction with recall, the percentage of relevant "collapsed" predictions returned by the proposed method. Recall R is defined by equation (9).

\[ R = \frac{A_r}{(A_r + A_g)} \]  

(9)

5.4 Experimental Results

Figure 9 presents the results for estimation of collapsed buildings. We find that there is a large number of collapsed buildings and that our proposed method is able to detect most of them. Tables 1, 2, and 3 show the actual percentages of Figure 9.

![Figure 9. The experimental results for estimation of collapsed buildings.](image)

| Table 1. Percentages for Minamisanriku Town (Figure 9-(a)) |
|----------------------------------------------------------|
| Actual Damage   | Total          |
|                | Collapsed | Not-Collapsed |              |
| Proposed Method |          |              |              |
| Collapsed       | 0.822     | 0.012        | 0.834        |
| Not-Collapsed   | 0.166     | 0.000        | 0.166        |
| Total           | 0.988     | 0.012        | 1.000        |

| Table 2. Percentages for Rikuzentakata City (Figure 9-(b)) |
|----------------------------------------------------------|
| Actual Damage   | Total          |
|                | Collapsed | Not-Collapsed |              |
| Proposed Method |          |              |              |
| Collapsed       | 0.826     | 0.083        | 0.909        |
| Not-Collapsed   | 0.066     | 0.025        | 0.091        |
| Total           | 0.892     | 0.108        | 1.000        |

| Table 3. Percentages for Kamaishi City (Figure 9-(c)) |
|----------------------------------------------------------|
| Actual Damage   | Total          |
|                | Collapsed | Not-Collapsed |              |
| Proposed Method |          |              |              |
| Collapsed       | 0.288     | 0.191        | 0.479        |
| Not-Collapsed   | 0.142     | 0.379        | 0.521        |
| Total           | 0.892     | 0.570        | 1.000        |

In tables 1 and 2, the results had high overall precision. In table 1, the percentage of correct answers is 0.823, precision is 0.986, and recall is 0.832. In table 2, the percentage of correct answers is 0.850, precision is 0.908, and recall is 0.926. However, the results in table 3 are not as good as in tables 1 and 2. The percentage of correct answers is 0.667, precision is 0.602, and recall is 0.670.

In this evaluation method, there are two different types of incorrect answers. One is that the proposed method classifies a building as collapsed, but the actual building has not collapsed. This error occurs when the threshold for detecting straight lines in the Hough transformation is not met. It is necessary to integrate a different technique for line-detection to solve this problem.

The other incorrect answer in when the proposed method classifies a building as non-collapsed, but the actual building has collapsed. The reason for this result is due to a difference in patterns of collapse between figure 9-(c) and the other two images. Figure 10 presents specific examples of incorrect answers in each image.
Figure 10-(a) is specific example of collapsed buildings from figure 9-(a) and 9-(b). The houses have collapsed without a trace. In this case, the error occurred because the road was falsely detected as straight lines of a roof. However, the roof of the collapsed building is clearly visible in figure 10-(b), which shows specific examples of collapsed buildings from figure 9-(c). This error occurred for 20 buildings out of 25 erroneous classifications. This error cannot be resolved when using our method with aerial photographs. However, these errors occur in less than 10% of the 361 total buildings in the image.

6 Discussion
In this section, we present a discussion from the perspective of evaluating disaster debris in affected areas.

Table 4 presents approximate estimations of total waste volume from the previous images using the proposed method.

|                  | Minamisanriku Town | Rikuzentakata City | Kamaishi City |
|------------------|---------------------|--------------------|---------------|
| A) Actual damage$\times 10^4$ ton | 68.2                | 65.9               | 15.7          |
| B) Proposed method$\times 10^4$ ton | 57.6                | 67.2               | 17.5          |
| B/A              | 0.843               | 1.012              | 1.113         |

In a massive disaster, it is difficult to estimate the amount of debris immediately. For example, we can examine the Great East Japan Earthquake. Some researchers attempted to estimate the total amount of debris. Hirayama researched a method of estimating debris extensively. However, the estimated amount of debris in that study was approximately 1.5 times the actual amount of debris.

If we can more exhaustively estimate debris, the system will become more practical and achieve better accuracy. Parallelization and high processing speeds will be required to achieve this task.

7 Conclusion
We proposed a system that detects collapsed buildings using aerial photographs taken after a disaster in order to estimate the amount of disaster debris. To detect collapsed buildings using aerial photograph, we extract straight lines (assuming they represent the roofs of buildings) from the photographs. Subsequently, we applied the proposed method to real aerial photographs that were taken in affected areas immediately after the Great East Japan Earthquake. Our proposed method achieved higher accuracy for estimating amounts of disaster debris when compared to existing methods. However, the performance of the extraction of roof features must improve for the system to become a practical application. In future research, we will consider image features other than straight lines. Parallelization and improved processing speed will be required to achieve this task.

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