Detecting the 3D Damaged Area of Historic Pagodas Using Vanishing Point

Thida Aung, Myint Myint Sein
University of Computer Studies, Yangon
aung.demon85@gmail.com, myintucsy@gmail.com

Abstract

Detecting the damaged area is the critical task for recovery and reconstruction work. Traditional damage detection or change detection method focus on two dimensional changes detection, whereas the two dimensional information delivered by the images is often not sufficient and accurate when dealing with building damage detection. In 24th August of 2016, the magnitude 6.8 earthquake struck at the historic city of Bagan, Myanmar. It caused huge damaged portion in historic pagodas in Bagan. The proposed method aims to detect the damaged area of the ancient pagodas after the earthquake. The point clouds output from the Pix4D software are used to input the system. The unnecessary point clouds are eliminated and calculate the damaged percentage of the specific pagodas. The post 3D images and their point cloud are used to estimate the damaging area. The purpose system detects the percentage of the damaged portion of the whole pagoda.

Keyword*: unnamed aerial vehicle (UAV); 3D image; 3D point clouds, damaged Area*

1. Introduction

Detailed damage assessment after the disaster has become the critical task in effective emergence response and recovery. In emergence response and recovery, manual assessment is expensive and time consuming. Sometimes urgent response is impossible in response. Remote sensing and geographic information system (GIS) is the useful alternative way for damage assessment process. We can get easily the satellite and aerial images (UAV images) after the disaster happened. We can get the urgent damage assessment using the combing the GIS technologies and digital image processing. Nowadays, in digital image processing many techniques are used to detect damages caused by natural hazards such as landslide, earthquake, fire and flood and so on. There are generally two kinds of detecting the damages; object-based damaged detection and region-based damaged detection. Object-based damaged detection emphasizes the shape, textures, background information and spectral information of the specific image [1]. Conventional change detection methods were mainly developed on radiometric information analysis of multi-temporal remote sensed spectral or optical images. Many applications such as monitoring land use/land cover classes, disaster assessment are developed by using change detection techniques. Change detection results using only 2D image information are often impacted by a significant amount of false alarms mainly caused by seasonal variations, different weather conditions, shadows and occlusions. Traditional building damage change detection is mainly focused on 2D change techniques especially based on the appearance of the image. In 2D change detection technique can calculate the changed and unchanged area of the building but is not sufficient and accurate the whole building change detection. So the detection of the building damage is desired based on the 3D features on 3D point clouds obtained from aerial images [2]. Due to the similar spectral characteristics, it is difficult to distinguish buildings from other artificial constructions as bridges and roads. Moreover, 2D image information based methods cannot be easily used to determine the changes at an individual building level and explore the volumetric information changes. Therefore, research on change detection on 3D point clouds remains an active topic and new techniques are demanded to effectively use available data from satellite, airborne, even low altitude platforms [5]. Many papers and techniques are proposed to detect the damage portion of the whole building. Most of them are based on the geometric mathematics especially vanishing points and vanishing parallel lines of the 3D building. The vanishing point is the intersection of two or more parallel vanishing lines. To detect the vanishing points and vanishing lines, there are generally many methods that are classified depend on the nature of images, the characteristics information of the images and the objects' location in the images. There is a lot of training time in the image-based vanishing point detection method. The characteristic-based method need the large computing time for the geometric calculation [7]. Meizhang He et al. [8], proposed the 3D shape descriptor to detect the surface damage and structural damage of individual roof. This descriptor identifies the spatial patterns of regular contour of the roof from airborne LiDAR point clouds. This proposed method cannot specify the different damage types of damaged roof by improving the shape analysis between contours.

Sara B. Walsh et al. [9], proposed the extended work including shape feature detection and segmentation and removing the outlying 3D point clouds. This system develops generic description of object based detection on range data of a collapsed bridge. H. Shusong et al. [7], proposed a nearest point searching method mechanism based on 2D projection plane of 3D point cloud data. The principle is searching point on building roof in the coordinate O-xyz, the point on projection plane is in the coordinate O-xy, search k-nearest point on this projection plane, then find these k-nearest original points in O-xyz and calculate the normal vector. This method can avoid the influence of height change caused by earthquake during search the nearest points. Xuehui Chen et al., proposed a new vanishing point detection algorithm based on Hough Transform for 3D reconstruction of a scene using no calibrated cameras. The positions of vanishing points can be calculated by corresponding to the line parameters in pole coordinate using the Hough Transform.

In this paper, the introduction is shown in Section 1. The section 2 explains the 3D Damaged Change Detection procedure of the proposed method. Experimental Result is mentioned in Section 3. Finally the conclusion of the purposed method is discussed in Section 4.

2. 3D Damaged Change Detection

In this Section, we describe the proposed system with the six main processes in the proposed system as shown in Figure 1.

(1) Extracting the boundary region for the specific pagoda from the 3D input point clouds
(2) Removing the Outlier point-clouds
(3) Finding the Vanishing Points
(4) Estimate the Volume of Pagoda
(5) Compare with Volume of Pagoda before disaster
(6) Compute Percentage of Damaged Region of the specific Pagoda

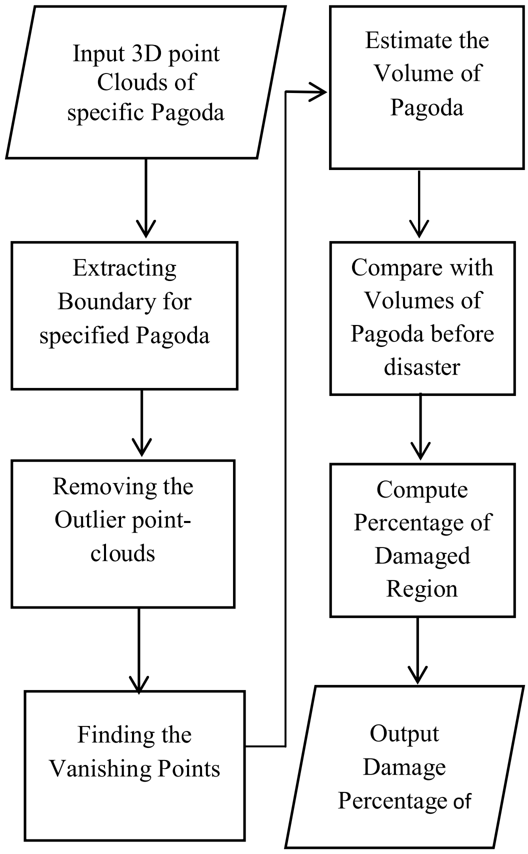

Figure 1. System Flow Diagram

2.1. 3D Change Detection with point clouds of UAV images

3D point clouds with height information can provide certain advantages over 2D imagery in disaster response. Some features and changes, such as soft-story failures where buildings collapse directly on top of weaker, lower floors, are undetectable in two dimensions from nadir [3]. Creating 3D surface models of disaster areas can overcome these obstacles in addition to providing the information obtained from 2D imagery. To determine the volume of the 3D pagodas, the vanishing points are found using the equations (8) and (9). The point cloud of Sulamuni Pagoda in 3D dimension is shown in figure 2. One of the four control points can be selected to input the next step, extracting the boundary. A vanishing point is a point in the image plane where the collection of parallel vanishing lines is interested.

2.2. Extracting the Boundary Region of Specific Pagoda

The numbers of 3D point clouds are generated by Pix4D software form the aerial images. That point cloud datasets contain varying point densities. Therefore the sparse outliers deduce the system's result even more. Some of outlier noise can be solved by using a statistical analysis on each 3D point cloud's neighborhood, and dropping out the unnecessary points cloud.

The unnecessary points can be calculated on the computation of the distribution of points in the input dataset. The outliers are trimmed based on the Median Absolute Deviation (MAD) with a mean and standard deviation. After eliminating the unnecessary point clouds, the output from the extracting boundary of Sulamuni pagoda is shown in figure 3.

Median absolute deviation (MAD) is a measurement of the variability of a univariate quantitative data in statistics. The population parameter can be estimated by calculating the MAD on the quantitative data. $X_1, X_2, ..., X_n$ are the univariate data set. The MAD is calculated from the median of the absolute deviations from the data's median:

$$MAD = median(|X_i - median(X)|) \tag{1}$$

MAD is the median of their absolute values. The median absolute deviation is a measure of statistical dispersion of the data. The MAD is a robust statistic, being more resilient to outliers in a data set than the standard deviation. In the standard deviation, the distances from the mean are squared, so large deviations are weighted more heavily, and thus outliers can heavily influence it. In the MAD, the deviations of a small number of outliers are irrelevant [6].

MAD is more critical to calculate the statistical facts from the dispersion of the data. MAD is related with the standard deviation for the equation (1). In the equation, k is a constant scale factor depending on the distribution.

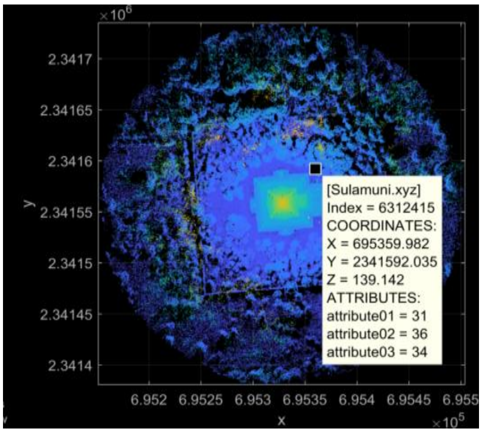

Figure 2. Selecting the one of Control Points

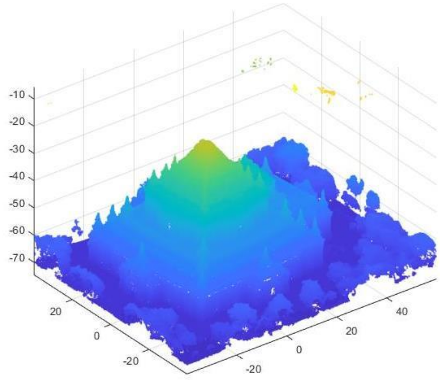

Figure 3. Point Clouds After Boundary Extraction

$$\sigma = k \cdot MAD \tag{2}$$

For normally distributed data k:

$$k = 1/\left(\phi^{-1}(3/4)\right) \approx 1.4826 \tag{3}$$

where ϕ^{-1} is the inverse of the cumulative distribution function for the standard normal distribution $Z = X/\sigma$.

$$\frac{1}{2} = P(|X-\mu| \le MAD) = P\left(\left|\frac{X-\mu}{\sigma}\right| \le \frac{MAD}{\sigma}\right) = P\left(|Z| \le \frac{MAD}{\sigma}\right) \tag{4}$$

The relation between the MAD and standard deviation can be calculated by finding k value firstly as shown in equation (5) and (6) respectively.

$$\left(\frac{MAD}{\sigma}\right) = 1 - \phi^{-1}\left(\frac{3}{4}\right) = 0.67449 \tag{5}$$

$$k = \frac{1}{\phi^{-1}\left(\frac{3}{4}\right)} = 1.4826 \tag{6}$$

The equation below (7) is for the MAD with standard deviation.

$$MAD = \sigma\sqrt{2}erf^{-1}\left(\frac{1}{2}\right) \approx 0.67449\ \sigma \tag{7}$$

2.3. Finding the Vanishing Point

The nature of vanishing points can provided much useful information for the 3D structure of the object. The key idea for finding the vanishing points is to detect the place where lines intersect. Therefore, the parallels lines should be detected in the point cloud of the 3D object. The points at which the number of parallel lines intersects and these points have become the vanishing points of the 3D object [4]. In detecting the vanishing points, there are two problems; the search space is unlimited and the vanishing points are at infinity. A line of 3D point represented as the following equation:

$$X(\lambda) = A + \lambda D \qquad (8)$$

Using $x = f\, X/Z$ the vanishing point of its image is

$$v = \lim_{\lambda \to \pm\infty} x(\lambda) = f\,\frac{A + \lambda D}{Az + \lambda Dz} = f\,\frac{D}{Dz} = f\begin{pmatrix} \frac{Dx}{Dz} \\ \frac{Dy}{Dz} \\ 1 \end{pmatrix} \qquad (9)$$

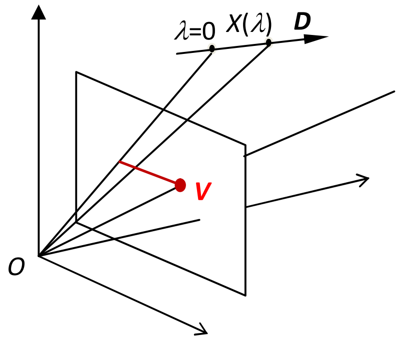

Figure 4. Relation of 3D Vanishing Points

In the explanation, (1) V depends only on the direction D, not on A. (2) Parallel lines have the same vanishing point [5].

3. Experimental Result

The study area is Bagan, the ancient capital of Myanmar, where occurred magnitude 6.8 earthquake in August 24, 2016. The Figure 5 shows one of the damage pagodas in Bagan. The total of 400 pagodas is damaged after the earthquake and the data collection for taking the aerial photos of damaged pagodas was performed by GIS Lab from University of Computer Studies, Yangon.

There are about 300 aerial photos for the specific damaged pagodas and each of which has 72 dpi horizontal and vertical resolutions. The point clouds are generated using pix4D mapper software from approximately 300-400 aerial images.

Figure 5. One of the Damaged Pagodas, Bagan, Myanmar

To calculate the percentage of damaged region of historical pagoda, firstly width, height and length of the individual pagoda are collected from web information and also collected as ground truth data. Some geographic information is available on historical database of the Ministry of Cultural and Religious affairs, Myanmar.

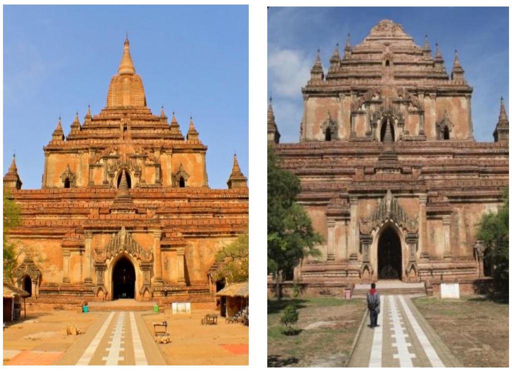

Figure 6. Sulamuni Pagoda Before Earthquake and After Earthquake

Figure 6 illustrated the pre and post images of Sulamuni pagoda. After the volume comparison of pre and post-earthquake of the specific pagoda is performed, the damaged percentage can be calculated as the equation (10) and the damage result of specific pagoda is shown in figure (7) and (8).

$$DamagedPercentage = \left(\frac{numberOfDamagedPixels}{numberOfTotalPixels}\right) \cdot 100\% \qquad (10)$$

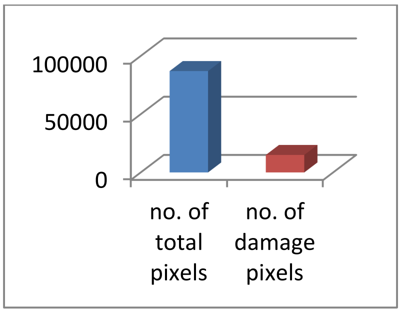

Figure 7. The Damaged Pixels Result of Sulamuni Pagoda

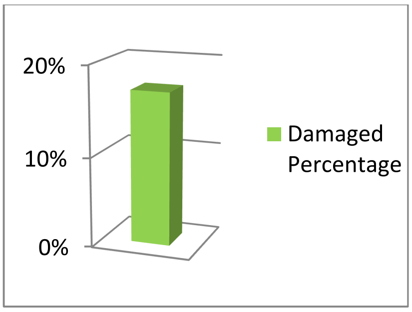

Figure 8. Damaged Percentage of Sulamuni Pagoda

4. Conclusion

Using 3D change detection which high density point clouds, many of these restrictive requirements are overcome. 3D change detection can reveal change that is undetectable in the traditional 2D space. Using high density point clouds, the changes that result in height differences are detected in the analysis. This creates very clean change detection, and allows focusing only on the important changes, and not be distracted by marginal changes. But some of the pagoda's edge points can easily be recognized as damage percentage. To acquire higher quality detection results, integrated detection and analysis of pagoda damage should be combined with structural texture analysis in the future.

References

[1] Thida Aung and Myint Myint Sein, "Change Detection of the Building areas in Urban Regions", 14th International Conference on Computer Applications (ICCA2016), Yangon, February 2016, pp. 124-130.

[2] Thida Aung and Myint Myint Sein, "Analysing the Disaster", The 10th International Conference on Genetic and Evolutionary Computing (ICGEC 2016), November, 2016, Fuzhou, China.

[3] Thida Aung and Myint Myint Sein, "Detection the Urban Changing Areas of Yangon City Using Landsat Time series Images", 15th International Conference on Computer Applications (ICCA2017), February 2017, Yangon.

[4] Myint Myint Sein and Hiromitsu Hama , "Recovering the 3D BSpline Control Points of the Free Curves for Shape Reforming", IEICE Translation on Information and Systems, Vol. E84D, No.8,August, 2001, pp.983989.

[5] Myint Myint Sein and H. Hama, "Analyzing the Segments of the Fragments for Recostruction of the Broken Earthenware", The SICE Annual Conference 2005, Okayama, Japan, Aug. 46, 2005.

[6] Myint Myint Sein and Yoshiki Arakawa, "Determining the Depth Measurement for the 3D Model Reconstruction", Proceeding of the SICE Annual Conference 2003, Fukui, Japan, pp. 865-868, Aug. 46,2003.

[7] H. Shusong, D. Aixia, W. Xiaoqing, W. Jinxia, "Earthquake-Induced Building Damage Detection Method Based On Normal Computation Of Neighboring Points Searching On 2d-Plane", IEEE International Geoscience & Remote Sensing Symposium, 2016, pp. 4251-4254.

[8] H. Meizhang, Q. Zhu, Z. Du, H. Hu, Y. Ding, M. Chen, A 3D Shape Descriptor Based on Contour Clusters for Damaged Roof Detection Using Airborne LiDAR Point Clouds, Remote Sens. 2016.

[9] Sara B. Walsh & Daniel J. Borello, B. Guldur, Jerome F. Hajjar, "Data Processing of Point Clouds for Object detection for Structural Engineering Applications", Computer-Aided Civil and Infrastructure Engineering, 2013.