Building Damage Assessment after the Earthquake in Haiti using two Post-event Satellite Stereo imagery and DSMs

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Abstract—**In this paper, a novel disaster building damage monitoring method is presented. This method combines the multispectral imagery and DSMs from stereo matching to obtain three kinds of changes. The proposed method contains three basic steps. The first step is to segment the panchromatic images to get the smallest possible homogeneous regions. In the second step, based on a rule based classification using change information from Iteratively Reweighted Multivariate Alteration Detection (IR-MAD) and height, the changes are classified to ruined buildings, new buildings, and changes without height change (mainly temporary residential area, etc. tents). In the last step, a region based grey level co-occurrence matrix texture measurement is used to refine the third change class. The method is applied to building change detection after the Haiti earthquake.**

I. INTRODUCTION

Building damage assessment is very important after natural disasters, like earthquakes or floods. There is a demand for updating existing databases and providing urban changes after the disasters. Remote sensing techniques are providing possibilities for change monitoring [1]. A popular technique to obtain the changes after a disaster is to compare the pre-event Very High Resolution (VHR) imagery with the post-event VHR imagery [2-3]. But many collapsed buildings can hardly be distinguished in the high dense building areas due to the fact that many destroyed buildings still share similar spectral radiometric information with unchanged buildings and roads. Moreover, it can be very difficult to separate building changes with other land cover changes without height information.

In order to overcome these problems, height information from DSM has been employed in disaster monitoring in many applications. [4] used the DSM from LiDAR data in extracting the building boundaries, which can be compared with existing pre-event building footprint data in getting a change map. Other researchers directly used two LiDAR DSMs to calculate the height changes [5].

Due to the high cost of LiDAR data, and low availability of building footprint data, these methods can be hardly applied for most areas of disaster assessment around the world. [6][7] tried to use the DSM from stereo imagery, but the test area they used is much simpler than most real cases (shown in Figure 1), and only direct DSM subtraction was used in generating the change map. Thus the detection results are highly dependent on the quality of the DSM, which may contain blunders.

Figure1. Example of the changes in high dense building area

The purpose of this paper is to present an approach for the monitoring of collapsed buildings and newly-built constructions after the earthquake in Haiti by using two pairs of post-event stereo imagery. One was acquired directly after the earthquake and the other is acquired half a year later. After half a year, many of the collapsed buildings were removed or rebuild, and some quickly built buildings and tent areas are constructed. These temporary living places are always located in parks or on squares after cutting down some trees or cleaning some small collapsed buildings. Therefore, the appearance of these temporary buildings may not lead to height change but only spectral and texture change. The monitoring of the removed buildings can give better destroyed building assessment, and the monitoring of new buildings and temporary buildings can also help government management and city planning.

We adopt a region based change detection method in this paper. To eliminate the influence from vegetation and shadows, we use a classification process before segmentation. After that the mean-shift segmentation is implied to get small region units. We use IR-MAD to combine the change vectors from images and DSM, and then they are classified in to collapsed buildings, new buildings and temporary buildings. In order to refine the third class changes, we use a region based texture measurement to refine the change class (change without influence of height).

II. DATASETS

A Very strong earthquake in Haiti on 12 January, 2010 led to heavy damages to buildings. We choose an area in Port-au-Prince for our research. Two dates of GeoEye-1 stereo images are used. One was obtained 6 days after the earthquake, and the area chosen contains many collapsed buildings. The second was acquired on 18 August, 2010. Many collapsed buildings are in the process of re-construction. In addition, in the August data many high dense tent areas can be found, which are built for the local residents.

(a)

(b)

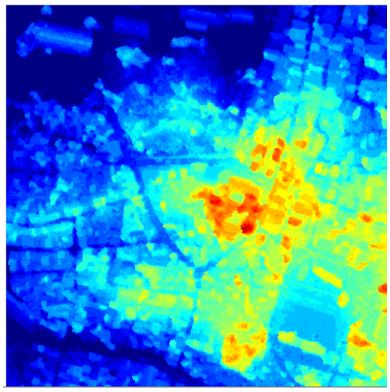
Figure 2. Panchromatic images of the test area ((a) Just after the earthquake; (b) Six months after the earthquake)

III. METHODOLOGY

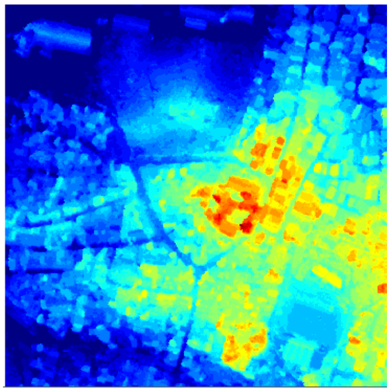
The DSMs generated from stereo data show lower quality than DSMs from LIDAR data, especially in high dense building areas. The aim of this paper is to generate a robust damage assessment map by fusing the height change information from space borne DSMs with lower quality together with texture information from ortho-rectified satellite images.

A. Proprocessing

The DSMs used in this paper are generated by the Semi-Global-Matching (SGM) method, which shows robustness and high matching density. It has been implemented in several versions, among which we use the one developed by d'Angelo et al. [8-9]. The DSMs from two dates are firstly co-registered to remove any shift in three dimensions.



(a)



(b)

Figure 3. Generated DSMs of the test area ((a) Just after the earthquake; (b) Six months after the earthquake)

As can be seen from Figure 3, roads and buildings can be roughly separated according to the height information. However, we cannot get a clear boundary due to the high building density. Moreover, in this situation, direct height subtraction will not be sufficient, due to low sharpness in building representation.

B. Segmentation

The original homogeneous regions are produced by applying segmentation separately to the images of both dates. Here, the objective of segmentation is to produce small units that have different spectral characteristics from the areas nearby. Many segmentation methods have been introduced in computer vision, like watershed, level-set, mean shift [10] and several more. However, automatic methods can hardly reach a proper level of segmentation with all classes well-separated from each other, since different kinds of objects require different segmentation levels. In this paper, first an over segmentation is generated using the mean shift algorithm from EDISON library [10] to obtain potentially small change units. In the segmentation procedure, we have used the land cover classes (shadow and vegetation. etc.) from multi-spectral images. Since the boundary of the collapsed buildings is better displayed in the January image and the boundary of the new build house is shown in the August images. Therefore, the segmentation procedure has been applied to them individually.

C. *Change classification*

Nielsen [11] introduced Iteratively Reweighted Multivariate Alteration Detection (IR-MAD) method to highlight the changes. It has been proven to be an effective linear change detection method. The main aim of this method is to establish a better background of no change, thus to identify the real changes.

As the most important advantage, IR-MAD is an unsupervised change detection method. It considers all of the feature channels generated from the images (DSM, texture, spectral channels, etc.) of the two dates F=$(F_1, F_2, F_3, \ldots F_k)^T$ and G=$(G_1, G_2, G_3, \ldots G_k)^T$. The changes can be expressed by the linear combination of the features from two dates (shown as Equation (1)). a_i and b_i are the coefficients calculated by applying Canonical Correlation Analysis.

$$\begin{bmatrix} F \\ G \end{bmatrix} \Rightarrow \begin{bmatrix} a_1^T F - b_1^T G \\ \cdot \\ \cdot \\ \cdot \\ a_k^T F - b_1^T G \end{bmatrix} \qquad (1)$$

IR-MAD is an iterative scheme to put high weights on areas with little change. This weight will be included in the calculation of mean, variances and covariance. The iteration will stop when the largest absolute change in the canonical correlations reaches a preset value e.g. 10^{-6}. We use the chi-square distance of all of the MAD components as the extracted change map.

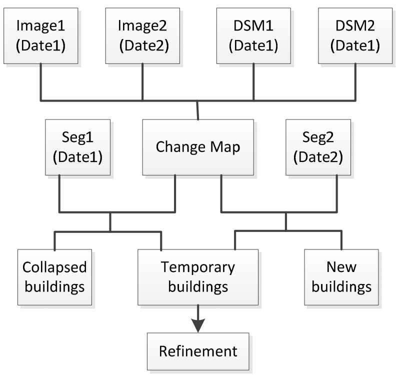


Figure 4. Change classification workflow

As shown in Figure 4, besides the multi-spectral bands of the satellite image, we use the panchromatic images and the DSMs as the original image features. As shown in Figure 4, the generated change map will be combined with the segmentation result from two dates respectively to classify the changes. The changed regions with height decrease are classified as collapsed buildings, and the regions that have height increase are classified as the new build ones. These regions exhibit high values in the change map, while no changes in height combined with change in multispectral data is classified as temporary buildings. Due to the large amount of regions belonging to the temporary buildings, a texture based refinement is done to improve the overall accuracy.

D. *Refinements using region based GLCM texture*

Gray level co-occurrence matrix (GLCM) is one of the popular and robust texture features. It estimates the second order statistics properties by calculating the frequency of pixels in different levels co-occurrence in a designed distance with in a given window [12]. In many cases, the window size will directly influence the efficiency of the usage of texture features. In this paper, instead of selecting the window size, we calculate the region based GLCM features. All of the pixels inside one region are used in the co-occurrence matrix generation. After we get the co-occurrence matrix, the second order statistics can be derived from it. Here we use the 'homogeneity' feature since it has proven to show a good performance in building change detection [13].

$$\text{Homogeneity: } \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \qquad (2)$$

in which $P_{i,j} = \dfrac{V_{i,j}}{\sum_{i,j=0}^{N-1} V_{i,j}}$

$\boldsymbol{i}$ is the row number

$\boldsymbol{j}$ is the column number

$\boldsymbol{V_{i,j}}$ is the number of the occurrence in the GLCM matrix at the position (i, j)

$P_{i,j}$ stands for the normalized value of $V_{i,j}$.

IV. RESULTS

The change detection results based on the introduced method is shown in Figure 5. Figure 5a shows the detected collapsed buildings with a height decrease of more than 2 meters. Figure 5c shows the newly built buildings with a height increase of more than 2 meters. Figure 5b and 5d are the temporary buildings detected by using the segmentation results from date1 and date2 respectively. Many detected areas shown in Figure 5b and 5d are similar, but the shapes are different due to the changes during this half year. By comparing these two masks, the detected temporary building masks can be classified to 3 types: 1) detected in both masks; 2) only shown in the mask figure 5b; 3) only shown in the mask figure 5d. GLCM homogeneity features are calculated respectively based on the regions from these three classes.

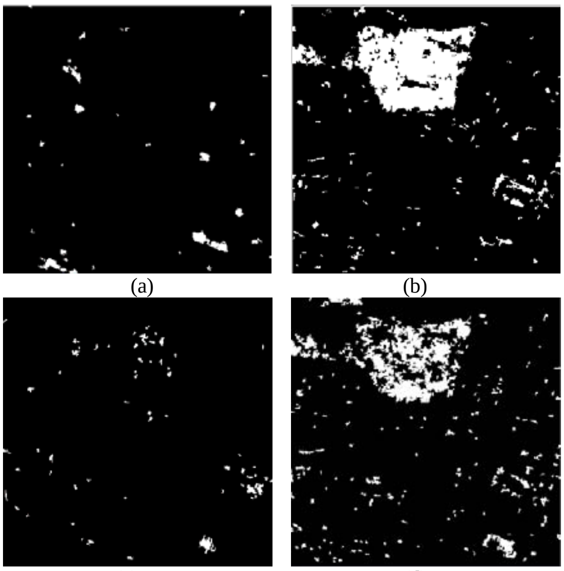


Figure 5. Original change mask ((a) collapsed building mask; (b) temporary buildings based on Seg1; (c) new building mask; (d) temporary buildings based on Seg2).

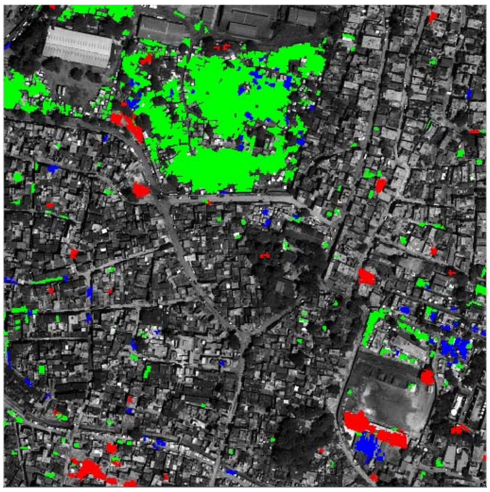


Figure 6. Change detection results (Red: collapsed buildings; Blue: New build buildings; Green: Temporary buildings.)

The final change detection result including the collapsed buildings (marked as read), newly built buildings (marked as blue) and temporary buildings (marked as green). This result has been projected onto the August Panchromatic image, as displayed in Figure 6. the detected change areas match well with visual interpretation of the image.

V. Discussion and Conclusion

The region based change detection method developed in this paper shows promising results when applied to monitor changes between two post-event satellite stereo imagery of the Haiti earthquake. It seems to be robust also in case of an urban area with dense buildings and small local changes. Three kinds of changes can be detected: collapsed buildings, newly built buildings and temporary buildings. All of these changes are essential for crisis management and scientific research.

The DSM from stereo matching can provide important height information in efficiently separating the collapsed buildings and newly built buildings. Panchromatic image based segmentation can classify the area into homogeneous regions. Using the average height from these regions can cover some quality drawbacks of the DSMs. Integration of the region based GLCM texture in change refinement has also worked to refine the change detection results especially for temporary buildings.

The developed methodology will in future be applied to compare the pre-event images and after-event images. It may give a rapid assessment of building changes in similar situations if stereo images are available.

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