SHADOW ANALYSIS IN ASSISTING DAMAGE DETECTION DUE TO EARTHQUAKES FROM QUICKBIRD IMAGERY

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ABSTRACT:

This study is to take the advantage of shadow appearance in Standard Imagery produced from QuickBird for damage detection in urban areas. In a very complex scene of an urban area acquired from very high resolution satellite-based optical sensors, fortunately, the buildings tend to align in some dominant directions in a small area and posses geometric regularity. Therefore, their shadows also align following these dominant directions in a small area in spite of the acquisition condition. The changes of building structures caused by an earthquake could affect the orientation, shape and size of its shadow. Two QuickBird scenes acquired over the city of Boumerdes, which was one of the most heavily-damaged areas due to the Algeria earthquake of magnitude 6.8 on May 21, 2003, are employed in this study. The first one was about one year before the event (April 22, 2002) and the second one was two days after the event (May 23, 2003). The result shows that the differences in shadow's lengths paralleling dominant directions can assist the detection of collapsed buildings. Moreover, unlike other classes of land cover in urban areas, the shadows can be successfully segmented by a conventional pixel-based classification method. The promising results from this analysis prove that shadow-based information could be used as a potential cue for automated detection of building damage.

1. INTRODUCTION

Damage detection plays an important role in disaster mitigation. It grasps the real situation after the events and provides the required information for further damage assessment. Hence, acquisition time, processing time, and accuracy of detection are vital. Remote sensing techniques providing the information in wide-coverage at a reasonable time gap after the events has been increasingly considered and employed. Recent researches in damage detection employing remote sensing can be listed into two directions. While the first direction is fusion of all available data sources as Casciati et al (1997) fused GIS, space- and airborne imagery, the second one develops methods for a specific kind of sensor. Typical examples of the latter are Hasegawa et al (1999) with aerial HDTV images, Matsuoka and Yamazaki (1999) with space-based optical and radar data. In the context of quick damage detection and consequently quick damage assessment, first trend seems not to be always feasible. The reasons are unsolved fusion methods and unavailability of GIS data in developing countries. Following the second direction, we are focusing in developing method for damage detection from very high resolution satellite imagery such as QuickBird. Furthermore, the trend of damage detection to automatic processing is also our final goal.

Providing very high spatial resolution imageries, QuickBird could provide enough detailed information for urban mapping and hence, it also presents more complex scene of urban areas. In such a scene, spectral information of building feature, which is our focus of interest, becomes diverse and ill-defined. Conventional pixel-based image classification such as parallelepiped, maximum likelihood, K-mean cannot produce a reliable detected result in processing multi-spectral high resolution satellite-based imagery (David and Wang, 2002). Object-based methods seem to be promising approaches but those methods have not been fully developed and implemented. Fortunately, at least pixel-based classification can successfully extract shadows. The stand of building casts the shadow in surrounding. In other words, shadows convey some aspect of information about buildings. The changes of buildings will affect the shadows of the buildings and it is probably the cue to assist the damage detection. Employing the well-developed pixel-based image classification and investigating the appearance of shadows to detect the damaged buildings are the focus of this study. The following section presents some observations which are the initial points for the shadow analysis. It is followed by the proposed methodology for shadow analysis, and testing result.

2. OBSERVATIONS

As abovementioned, Quickbird image presents very complex scene of urban area. However, behind this complexity, within a focused area, buildings tend to be aligned following some specific direction (Sohn and Downman, 2002). It was determined at the urban planning stage. Moreover, buildings usually possess geometric regularity such as rectangle. Therefore, building's shadows will align following longitudinal

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and transverse directions of the building. Figure 1 demonstrates a small area with extracted shadows of buildings and the aligned directions shown in FFT power spectrum.

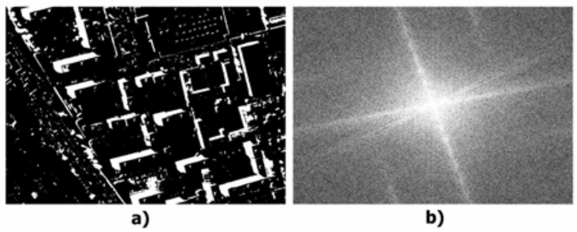

Figure 1. Example of dominant directions in focused area: a) extracted shadow scene and b) FFT power spectrum

When earthquake occurs, the strong ground motion will cause the damage of buildings. As a result, buildings might be fully collapsed, partly collapsed or its orientation might be changed. In those cases, the lengths of building's shadows along the dominant directions in focused area will be changed. Thus, length comparison between pre-event and post-event scenes can be one of the indicators for damage detection.

As shown in Figure 1a, the complexity of urban area also generates the complexity in extracted shadows. There are considerably large-size shadows generated by buildings or tree rows and small-size shadows generated by stand-alone trees, cars, or tents. Lack of spectral information from shadows, shape and size of shadows must be employed in discrimination analysis. Scale-space analysis, which takes scale property of objects into account, has been developed for decades (Lindeberg, 1993). Shadow analysis in this study concerns the changes of shadow lengths. Thus, the scale-space analysis should well preserve the details of each considerably large shadows but remove all small shadows. Non-linear scale space analysis based on area morphology has been proved to satisfy this requirement (Acton and Mukherjee, 2000). Briefly, area morphology scale space can be illustrated as follow.

Let set S defined on domain $\Omega \subset Z^2$. Area open $S \circ s$ remove all components of area less than s in the set S. Area close $S \bullet s$ remove all components of area less than s in the set S^c (complement of S). The scale space is constructed using AOC (area open-close) or ACO (area close-open) operators. Let I_s be the image representation at scale s, AOC (area open-close) scale space $\{I\}$ given by

$$I_s(t) = I_s(t-1) \circ s(t) \bullet s(t) \tag{1}$$

Given a scale space $\{I\}$, $I_s(x,y)$ is intensity at position (x,y) and scale s, to discriminate the shadows based on their size, we cluster $I_s(x,y)$ across the scale space. In this study, we simply apply K-mean clustering algorithm. Scale-space analysis employed in this study is like a non-linear filtering. Figure 2 demonstrates a result of area morphology scale space filtering. It shows a perfect preservation of object's boundaries.

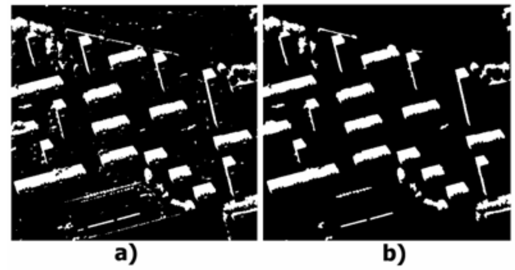

Figure 2. Example of area-morphology scale space filtering: a) Before filtering and b) After filtering

3. METHODOLOGY

Based on the above observations, we proposed an automatic shadow analysis, which compared the extracted shadows from pre-event and post event high resolution imageries to find out the cue for damage detection. This section presents only the core processing, which is fully automatic. There must be some pre-processing steps, which depend on the in-hand high resolution satellite imagery, before this automatic processing can be employed. Thus, the proposed method can be employed not only one kind of high-resolution satellite imagery.

Step 1: Extract both pre-event and post-event imageries in the small equal portions. Separately processing each small portion is not only to focus the analysis into specific dominant directions but also to speed up the processing. While area morphology scale space produces a perfect result (Figure 2), its shortcoming is time consuming (Acton, 2000). Processing in a small portion will be faster than a very big scene. Moreover, parallel processing can be employed.

Step 2: Apply area morphology scale space filtering as introduced in Section 2 for each portion.

Step 3: Concerning the boundaries of extracted shadows, dominant directions of each portion are computed. Examining the local window 3x3 of each pixel, the direction of each pixel is assigned follow the rules in Figure 3, where direction is represented in degree. Consequently, histogram analysis shows the dominant directions for each portion.

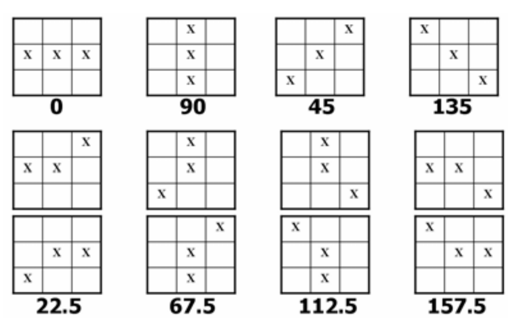

Figure 3. Distribution of boundary pixels in 3x3 local window and assigned angle

Step 4: Compute the lengths of shadow along the above specified dominant directions. Length comparison is carried out afterwards. Let $DiffL_1$ and $DiffL_2$ be the differences in lengths along two mentioned directions, these lengths are calculated as follows.

$$DiffL_1 = \left| postL_1 - preL_1 \right| \tag{2}$$

$$DiffL_2 = \left| postL_2 - preL_2 \right| \tag{3}$$

where $postL_1$, $postL_2$ = lengths of shadows from post-event image
$preL_1$, $preL_2$ = lengths of shadows from pre-event image
| | = function to take absolute value

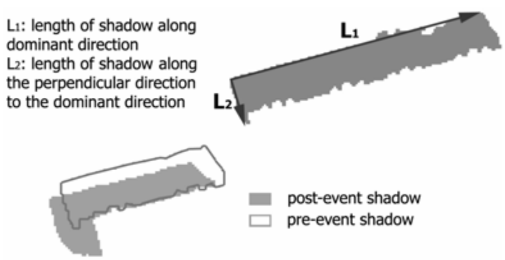

Figure 4. Illustration of length computation along dominant directions

Step5: Thresholding the differences in length. When one among two values of length difference is bigger than a threshold, it is probably due to the damage.

Step 6: Merge all extracted shadows from all portions with assigned label whether it is damaged or non-damaged.

4. TEST RESULT

The proposed methodology was employed for processing two pan-sharpened Quickbird scenes acquired over Boumerdes city, Algeria. Boumerdes was one of the most heavily-damaged areas due to the earthquake of magnitude 6.8 on May 21, 2003. The first scene was about one year before the event (April 22, 2002) and the second one was two days after the event (May 23, 2003). These scenes were in Standard format, which were terrain corrected. It means the ground features were correctly mapped, but the scene has not been ortho-rectified. When comparing two scenes, the roofs of the same building were not in the same location but their shadows were overlapped. Furthermore, there is a slight difference between these scenes due to difference acquisition condition. Prior to employing the proposed extraction method, these two scenes were co-registered and extracted into the same region of interest. Shadows were successfully extracted by K-mean unsupervised classification. The dimension of the test area was 3800 pixels x 2900 pixels (approximately 2200 m x 1700 m for pan-sharpened scene) (Figure 5).

Detected shadows are shown in Figure 6. However, visual checking both scenes, there was just about 50% of shadows really caused by buildings; others were by trees or even clouds (Figure 7). Further studies will consider the clearly discriminating between those kinds of shadow. If trees and buildings could be successfully classified, their shadows would be well discriminated.

Figure 5. Pan-sharpening Quickbird scene acquired on May 21, 2003 in true colour composite of the study area

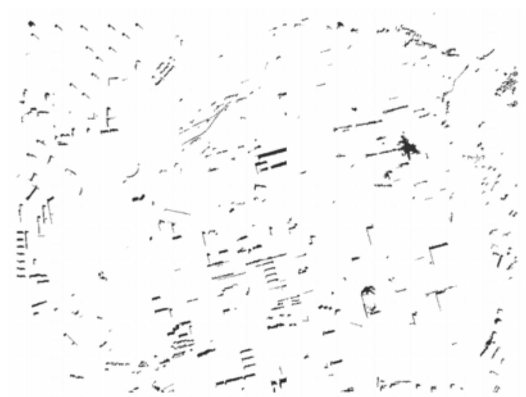

Figure 6. Detected shadows (post-event scene)

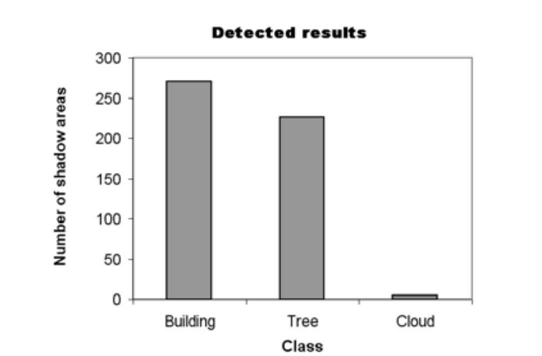

Figure 7. Distribution of detected shadows

Examining the scatterogram between two length differences of extracted shadows (Figure 8), the threshold of 10 m was chosen to classify damaged and non-damaged buildings. This result was compared to visual interpretation of Quickbird carried out by Kouchi et al (2004). As illustrated in Figure 9, there is highest probability to detect heavily damaged buildings by using only shadow analysis. Only 10 % - 20 % of slightly or moderate damaged buildings could be detected. A shorter threshold could increase the percentage of successful detection in damaged buildings but also increase the percentage of wrong detection in non-damage buildings.

In a very complex scene of urban area, only shadow analysis cannot produce an accurate detection. However, this analysis provided some aspect of information which has not been considered before. First, shadows were concerned as useful information for damage detection. Instead of directly comparing buildings, which are very difficult due to different acquisition condition, indirectly comparing through shadows could provide the cue for damage detection. Second, by automatic processing, shadow analysis can quickly point out the collapsed buildings. Last but not least, shadow analysis can be integrated in further developed damage detection method. The results from shadow analysis can guide the further analyses and also be clarified by these analyses, vice versa.

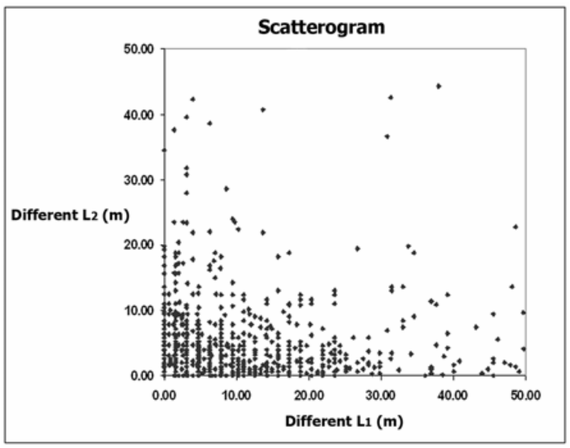

Figure 8. Scatterogram of two length differences

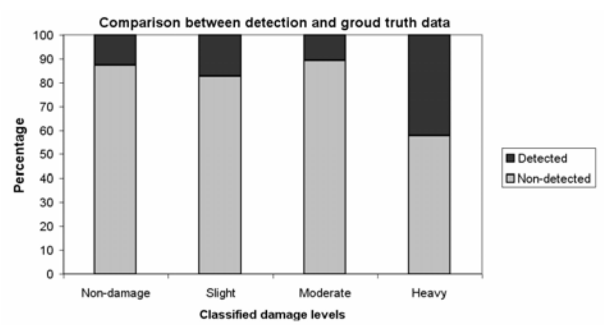

Figure 9. Distribution of detected shadows with respect to visual interpretation results

5. CONCLUSION

Automatic shadow analysis has been proposed, implemented and tested in Quickbird imagery. It was built to take advantage of shadow existence in the scene and to convert shadow to useful cue for damage detection. The test results showed high probability of shadow analysis in detection of heavily damaged buildings. Further testing in different sites can present more clearly the capability and limitation of shadow analysis. It is recommended to integrate shadow analysis, if applicable, into full developed automatic damage detection from high resolution satellite imagery.

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