EXTRACTION OF BUILDING DAMAGES IN THE 2007 NIIGATA-KEN CHUETSU-OKI EARTHQUAKE USING DIGITAL AERIAL IMAGES

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ABSTRACT: Remote sensing technology is effective to grasp the damage distributions from various natural disasters, such as earthquakes, tsunamis and volcanic eruptions. After the 2007 Niigata-ken Chuetsu-oki, Japan earthquake, aerial images were taken in the stricken area by several air survey companies in Japan. Airborne remote sensing is more suitable to collect detailed damage distribution because it provides higher resolution images than satellite remote sensing does. The post-event image taken by a digital aerial camera (DMC) is employed in this study to detect building damages. Although the accuracy of visual damage inspection is good enough, it takes time to perform for the whole areas that are subjected to severe ground motion. Therefore, in this study, the automated technique is proposed to extract building damages. The proposed technique is expected to contribute for the damage assessment at an early stage after the occurrence of an earthquake.

1. INTRODUCTION

Aerial photography has been used widely for aerial surveying and detecting damages due to earthquakes because of its very high spatial-resolution. Though the spatial-resolution of very high resolution satellite images, such as QuickBird and IKONOS, are 0.6m and 1.0m at the maximum, that of aerial images is higher than 0.1m. Recently, not only traditional analog (film) aerial cameras but also digital aerial cameras are used for aerial photography. Digital aerial cameras have much higher radiometric resolution than analog aerial cameras do. Consequently, even though the spatial resolution is almost the same level, digital aerial cameras can capture much clearer images than analog aerial cameras do. Due to this characteristic, digital aerial cameras have wider applications, e.g. objects in dark shadow and a bright area. Another important feature of digital aerial cameras is that they have a near-infrared (NIR) band as well as RGB visible bands. Using the NIR band, the extraction of vegetation becomes quit easy. Digital aerial cameras have these useful features.

Various studies have been performed using aerial images. Mitomi et al. (2002) and Maruyama et al. (2006) developed the method of detecting damages of buildings and highways, respectively, using the edge information from aerial images. Liu et al. (2007) detected the speed of vehicles using the time lag between two consecutive aerial images.

Damage extraction of buildings due to earthquakes has been performed extensively using high-resolution optical satellite images. Yano et al. (2004) conducted the visual inspection of individual building damage using QuickBird images from the 2003 Bam, Iran earthquake. Although the accuracy of visual damage inspection is good enough, it is time consuming and the results depend on interpreters. Hence, an automated damage extraction method is required to be developed. Kouchi et al. (2005) and Matsumoto et al. (2006) applied the pixel-based maximum likelihood classification and the object-based classification to detect damages of buildings using post-earthquake QuickBird images.

These approaches provide a certain level of accuracy, but the accuracy is limited to the resolution of QuickBird, 0.6m after pansharpening. Due to the higher spatial resolution, digital aerial images are more effective to detect detailed damages than QuickBird images are. In this paper, the pixel-based and object-based supervised classifications are applied to a digital aerial image obtained just after the 2007 Niigata-ken Chuetsu-oki, Japan earthquake and the accuracy of the damage extraction results is discussed.

2. THE NIIGATA-KEN CHUETSU-OKI EARTHQUAKE AND DIGITAL AERIAL IMAGES

The central part of Niigata Prefecture, Japan was hit by a strong $M_{JMA} = 6.8$ earthquake on July 16, 2007. A total 15 people were killed and 1,319 houses were collapsed in Niigata Prefecture. Kashiwazaki City was most severely affected in the prefecture with 14 people killed and 1,109 houses collapsed. Higashi-honcho block is located in the central part of Kashiwazaki City, with a shopping street and a surrounding residential area. We selected Higashi-honcho as an area to study because many old wooden houses in this block were collapsed or severely damaged, as shown in Figure 1.

Figure 2 shows a digital aerial image of Higashi-honcho, taken by Asia Air Survey Co., Ltd. on July 19, 2007 (three days after the earthquake). A DMC (Digital Mapping Camera) was used and it is one of the most popular digital aerial cameras in the world. DMC has a wide dynamic range with four (R, G, B, NIR) multi-spectral bands and one panchromatic band (Intergraph Corporation). The ground resolution of the image after pan-sharpening is 12.2 cm. The size of the image is 2,158 pixels in width and 1,350 pixels in height.

Figure 1 Location of Kashiwazaki City and the photos from the authors' field survey

Figure 2 Digital aerial image (DMC) of Higashi-honcho in Kashiwazaki (July 19, 2007)

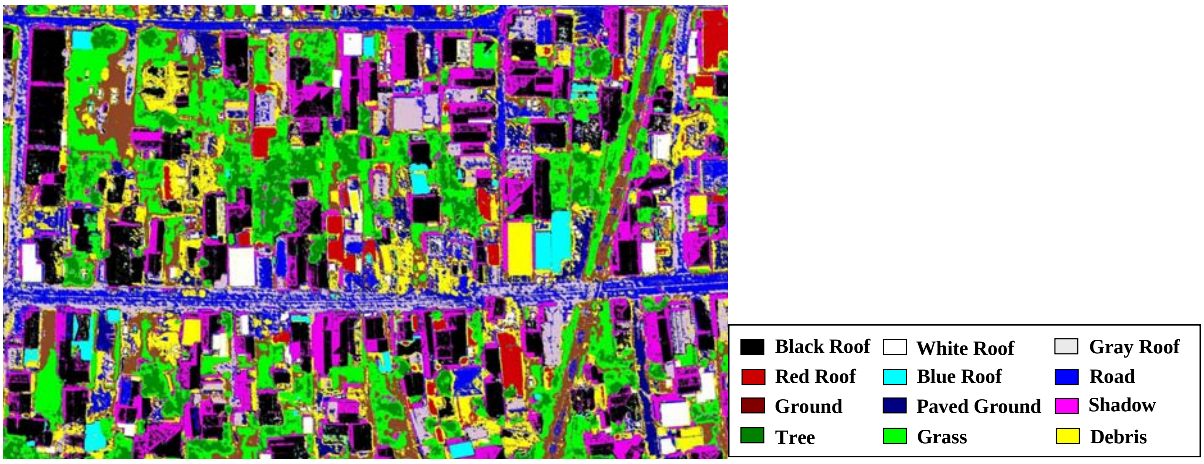


Figure 3 The result of pixel-based supervised classification

Figure 4 The results of automated damage extraction based on pixel-based classification (left) and visual inspection (right)

3. DAMAGE EXTRACTION OF THE STUDY AREA

3.1 PIXEL-BASED CLASSIFICATION

In order to develop an automated damage extraction technique, a conventional pixel-based classification was performed first based on the maximum likelihood method. In the classification, 8 bit values of RGB and NIR bands were used and twelve classes were selected as training data: *black roof*, *white roof*, *gray roof*, *red roof*, *blue roof*, *road*, *ground*, *paved ground*, *shadow*, *tree*, *grass*, and *debris*.

The result of the classification is shown in Figure 3. Vegetation areas (*tree* and *grass*) were correctly classified because the NIR band was used. However, salt-and-pepper noises are seen in all the parts of the image. Such noises were generated because the digital aerial image has very-high resolution which captures fine details, especially in pixel-based classification. Therefore, many small misclassifications are seen, especially for black-roofs by capturing individual roof-tiles. Another cause of misclassification is the effect of sunlight. Since sunlight comes from the right side of the image, the brightness of right- and left-side roofs is different.

Figure 4 shows the result of automated damage extraction based on pixel-based classification and visual damage extraction for the post-event image. The pixels classified as the debris class in the automated damage extraction were more than actual debris. Debris does not have unique spectral characteristics because it consists of the mixture of woods, mud and roof-tiles. Therefore, a lot of misclassifications as debris were seen in the ground and non-damaged roofs, which do not belong to

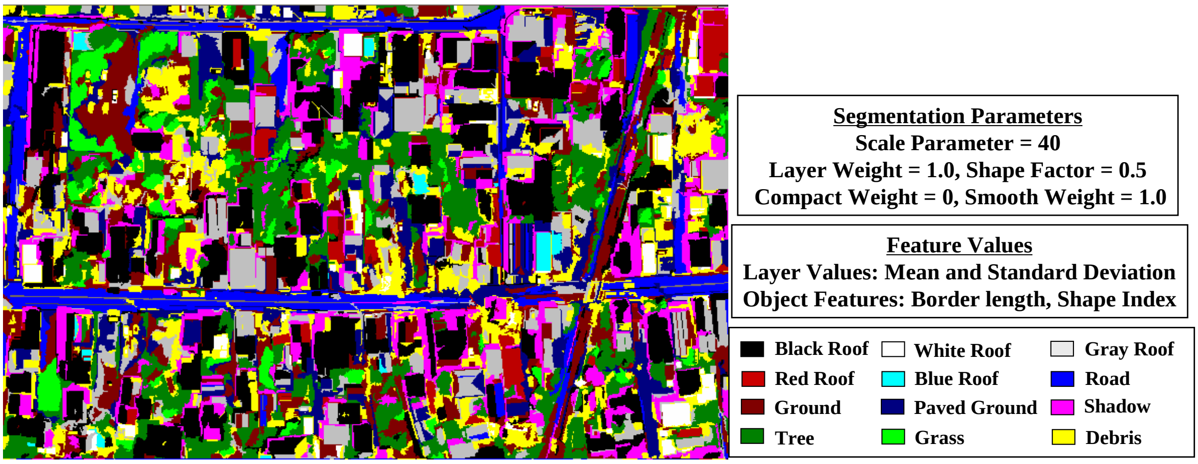


Figure 5 The result of object-based supervised classification and parameters used

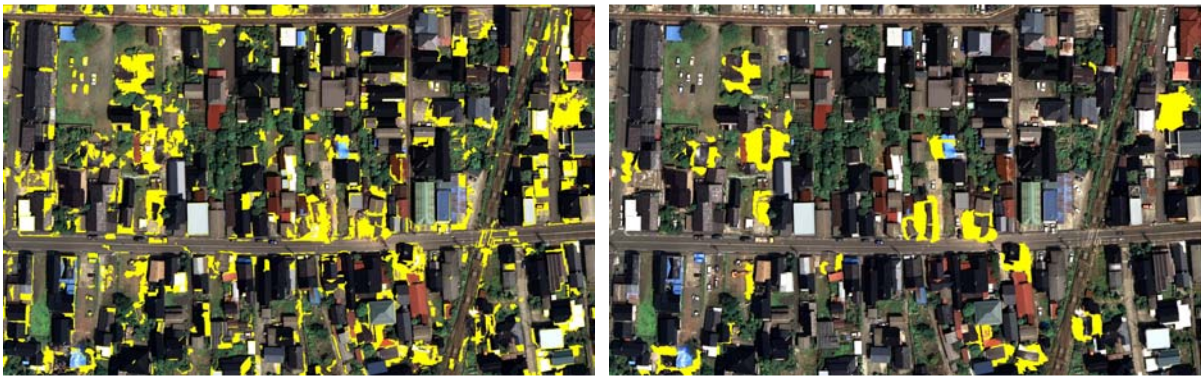


Figure 6 The results of automated damage extraction based on object-based classification (left) and visual inspection (right)

the roof-colors of the training data.

3.2 OBJECT-BASED CLASSIFICATION

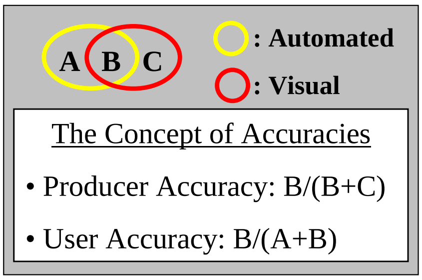
To solve the salt-and-pepper noise problem in high-resolution images, object-based classification has recently been introduced. In the classification, e-Cognition software (Definiens Imaging GmbH, 2004) was employed. In order to make "image objects", image segmentation, which merges neighboring pixels with a similar condition, was carried out as a first step. In this software, the segmentation process is determined by five parameters: *Scale Parameter*, *Shape Factor*, *Layer Weight*, *Compact Weight*, and *Smooth Weight* (Baatz et al., 2004).

Scale Parameter is the most important parameter controlling the size of image objects. *Shape Factor* determines the level of spectral heterogeneity and shape heterogeneity in the segmentation process. When *Shape Factor* moves toward its minimum value (0.0), spectral heterogeneity is more concerned. On the contrary, when it moves toward its maximum value (0.9), shape heterogeneity is more concerned. *Layer Weight* determines the spectral heterogeneity of each spectral band. *Compact Weight* and *Smooth Weight* determined the shape heterogeneity; the summation of these values should be 1.0. When *Compact Weight* is larger than *Smooth Weight*, the segmented image objects become a more round shape. On the contrary, when *Smooth Weight* is larger than *Compact Weight*, they become to have smoother borderlines. The appropriate parameters for the extraction of debris from this aerial image were determined by case studies and they are shown in Figure 5.

When the classification is performed, spectral characteristics of each band are the most important feature. Therefore, since the standard deviation of each band is large for the objects of debris, not only the mean value but also the standard deviation of each band were used in the classification. When classification is carried out in e-Cognition, not only these layer values of image objects but also various feature values of image objects (object features), such as the shape, can be considered. The characteristic object features of debris are with a very complex shape and a smaller area than others. In order to extract debris accurately, the object features, that are *border length* and *shape index*, were employed in the classification. The border length is the length of borderline of image objects and the shape index means the degree of complexity of image objects; if an image object has a complex shape, the shape index is given as a high value. The object-based classification used the same spectral bands and training data as the pixel-based classification did. But the nearest neighbor method was used in a classification step.

The result of classification based on these segmentation parameters and feature values is shown in Figure 5. It looks better than the pixel-based classification result because salt-and-pepper noises are no more seen and the outlines of non-damaged building roofs are very clear. However, the result includes some misclassifications and thus some additional processes may be necessary. Figure 6 compares the result of the object-based classification and that of the visual inspection. The image objects classified as the debris class were still larger than the actual debris areas, like the pixel-based classification result.

Table 1 Accuracies of automated damage extraction based on pixel-based classification and object-based classification



	Producer Accuracy (B/(B+C))	User Accuracy (B/(A+B))
Pixel-based	58.8%	18.9%
Object-based	60.7%	20.7%

3.3 ACCURACY OF AUTOMATED DAMAGE EXTRACTION

These accuracies of the damage extraction based on the pixel-based and object-based classifications were compared with the result of the visual damage extraction. The concept of the producer accuracy and user accuracy is defined in Table 1.

According to Table 1, the producer accuracies of the both methods are about 60%, which means more than a half of actual damaged areas can be extracted. On the other hand, the user accuracies of the both methods were about 20%, which means the area of “A” in Figure 7 is much larger than that of “B”. More pixels and image objects were extracted wrongly from non-damaged areas and, thus many commission errors occurred. When the accuracies of the two classifications were compared, the object-based method showed better accuracy than the pixel-based method did. However, their accuracies are still not so high as expected. Since the layer values and object features can be considered in the object-based classification, there is a room for improvement in this method. A future study using more examples may be necessary to improve the accuracy of debris extraction from digital aerial images of urban areas.

4. CONCLUSIONS

Automated building damage extraction was conducted using a digital aerial image captured after the 16 July 2007 Niigata-ken Chuetsu-oki, Japan earthquake. First, a pixel-based maximum likelihood classification was performed. In the pixel-based classification result, salt-and-pepper noises and misclassifications were seen. Second, an object-based classification was then performed using e-Cognition software. In this software, when classification is carried out, not only the spectral characteristics of image objects but also various features of them can be considered. But the result of the object-based method also includes some misclassifications. Finally, comparing with the visual inspection result, the accuracies of the debris extractions were evaluated. Although the producer accuracies were about 60% for the both methods, the user accuracies were low, about 20% for the both methods. To improve the accuracy of the debris extraction methods in the future, the features of debris should be considered more accurately. The methods should also be tested for larger areas and more examples.

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