Distributed and hierarchical object-based image analysis for damage assessment: a case study of 2008 Wenchuan earthquake, China

Jing Sun and Tuong Thuy Vu

Geoinformatics, Royal Institute of Technology, Stockholm, Sweden; School of Geography, University of Nottingham, Malaysia campus, Semenyih, Malaysia

ABSTRACT
Object-based image analysis (OBIA) is an emerging technique for analyzing remote sensing image based on object properties including spectral, geometry, contextual and texture information. To reduce the computational cost of this comprehensive OBIA and make it more feasible in disaster responses, we developed a unique approach — distributed and hierarchical OBIA approach for damage assessment. This study demonstrated a completed classification of YingXiu town, heavily devastated by the 2008 Wenchuan earthquake using Quickbrid imagery. Two distinctive areas, mountainous areas and urban, were analyzed separately. This approach does not require substantial processing power and large amounts of available memory because image of a large disaster-affected area was split in smaller pieces. Two or more computers could be used in parallel to process and analyze these sub-images based on different requirements. The approach can be applicable in other cases whereas the established set of rules can be adopted in similar study areas. More experiments will be carried out in future studies to prove its feasibility.

1. Introduction
To respond natural disasters such as earthquake or hurricane, capturing and identifying damage extent, distribution and level are essential for making decision, and implementing fast and effective recovery measures to limit the death toll and further property loss. Remote-sensing techniques provide timely responses over a large area, especially for hard-hit and difficult-to-access areas (Vu et al. 2005). High-resolution remote sensing imagery is proven effective in extraction of seismic damage information and quick damage assessment. Visual interpretation is the most reliable method and can derive accurate results, but very time consuming and requires of the experienced interpreters. Hence, quick damage detection needs to be developed (Sakamoto et al. 2004). In processing high-resolution remote sensing, the object-based image analysis (OBIA) is more appropriate. It takes into account not only the spectral information but also shape, texture, contextual, topological and semantic information with meaningful image objects (Burnett & Blaschke 2003; Wiseman et al. 2009). On the other hand, it can solve the problem of classifying complex objects, addresses the phenomenon of the same objects having different spectra and different objects having the same spectrum (Xie et al. 2008; Sun et al. 2010). Image segmentation, the first step of OBIA is to subdivide an image with determined criteria of homogeneity and heterogeneity in order to generate objects.
(Akçay & Aksoy 2008; Blaschke 2010; Martha et al. 2011). The next step is to assign objects to certain classes with various scales by implementing a knowledge-based hierarchy classification scheme (Shruthi 2011; Doxani 2012; Vieira et al. 2012; Sebari & He 2013). The capability to deal with complex issue pays a cost of computation. OBIA methods seem not a first choice in damage identification in post-disaster responses.

Wenchuan earthquake, with magnitude 8.0 on the Richter scale, duration of nearly two minutes, occurred on 12 May 2008 in the south-western Sichuan Province of China. More than 5 million buildings collapsed and other 21 million damaged at different degrees across a wide area (USGS 2008) and the number of earthquake casualties reached 87,000 dead or missing and 374,000 injured. After Wenchuan earthquake, multi-satellite sensor data were used to analyze landslides (Liu & Yamazaki 2008; Ren & Lin 2010), barrier lakes (Pan & Tang 2010), river change (Liou et al. 2010; Xu et al. 2010; Gong et al. 2012) and debris flow (Zhuang et al. 2010), building damage detection (Wang & Wang 2009; Li et al. 2010; Vu & Ban 2010). Most object identification of the seismic damage is relatively single, only focused on the destruction or collapse of buildings, especially residential buildings (Tiede et al. 2011). Though the outcomes were produced at certain degree of reliability, they could not provide the overall picture of damage and seems not practical in post-disaster response when time is critical (Hussain et al. 2011; Mondini et al. 2011; Aksoy & Ercanoglu 2012).

Taking the 2008 Wenchuan earthquake as a case study, we present a new distributed and hierarchical object-based image analysis for identification of earthquake damages. This approach could improve the speed of process and efficiency in quick response to major disaster situations, humanitarian relief efforts and civil security issues, especially for large affected areas. Image of a large disaster-affected area was split in smaller pieces using segmentation and classification. These pieces were subsequently distributed to different processors for parallel processing. In our study area, mountainous and urban areas were well distinctive. Landslide was observed in the former one whereas building structure damage was the main objects of interest in the latter. Landslide, which was visible at a synoptic view, was firstly delineated using a simple algorithm by detecting the change of vegetation between pre- and post-images. Damage features were identified and extracted following a structural framework consisting of hierarchical segmentation and knowledge-rule classification. Based upon different damage characteristics of the typical artificial surface features (buildings, roads and bridges) and secondary disasters such as landslides, different reasoning rules of earthquake damage identification and extraction were set for the whole region.

2. Data and study area

We focused the study in Yingxiu town (31.061°N, 103.333°E), Wenchuan county of Sichuan province (the red area shown in figure 1(b), approximately 10 km away the epicentre (30.986°N, 103.364°E and 19 km depth). The town was almost completely destroyed, included most of buildings, road networks and infrastructures. Two Quickbird images were used to detect the damage by the earthquake in Yingxiu town, we focused in area of approximately 2.1 km × 2.30 km. The pre-event image was acquired on 25 June 2005 whereas the post-event was acquired on 3 June 2008, and both consist of four multispectral bands with 2.44 m resolution and a panchromatic band with 0.61 m resolution. Two images were acquired in the same month to minimize seasonal effects. A 30-m-resolution digital elevation model (DEM) of Wenchuan County was downloaded from Geospatial Data Cloud (http://www.gscloud.cn/listdata/listdata_new.shtml?from = &productIds = 310#Wzg4LFswLDEwLDEsMF0sW10sW10sOT1d). The value of DEM was from 851 to 1375 meters.

3. Distributed and hierarchical OBIA (DH-OBIA) approach

Though the approach described here is following the characteristics of the study area, its general idea can be applicable to other cases. In this particular area, there are two clearly distinctive regions:
urban and mountainous. The 2008 Wenchuan earthquake caused severe damages to infrastructures (houses, bridges, etc.), only found in urban areas, and triggered big landslides in mountainous areas. The situation suggested an approach that splits the satellite image of the study area to two smaller distinctive pieces on which we focused in studying of different damage types. Multi-resolution object-based image analysis eCognition (Definiens 2009) was used together with other remote sensing and GIS packages for implementation of the proposed approach. Simple rule and processing approach are applied on coarse resolution large areas whereas more sophisticated processing approach was used for small fine resolution areas. Each level of resolution was generated using a region-growing segmentation procedure, starting from a single pixel; the merge of small objects to a bigger one is controlled by a scale factor $f$ (equation (1)). The scale factor is a combined parameter balancing between colour (or spectral), compactness and smoothness of the objects.

$$f = w \times h_{\text{colour}} + (1 - w) \times h_{\text{shape}}$$

(1)

where $w$ ranges from 0 to 1, $h_{\text{colour}}$ is the colour criterion and $h_{\text{shape}}$ is the shape criterion (equation (2)).

$$h_{\text{shape}} = w_{\text{compact}} \times h_{\text{compact}} + (1 - w_{\text{compact}}) \times h_{\text{smooth}}$$

(2)

In the first step, pre-event and post-event images were pre-processed, including otho-retification, geometry correction and pan-sharpening. After segmentation of the pre-image with a large-scale parameter since we did not focus to details at this stage, NDVI (Normalized Difference Vegetation Index) was used to classify the segmented pre-image into two classes: urban areas and mountainous areas. Based on the delineated boundaries, both the pre-image and post-image were split and distributed, generating four sub-images: mountainous areas full of vegetation around urban areas named Pre_veg and Post_veg (Group 1); and urban areas in the middle of the original images named Pre_nonveg and Post_nonveg (Group 2).

With Group1, our main attempt was to delineate landslide areas. Obviously, the clue is vegetation loss and steep slope. The former could be easily identified by change detection but the threshold chosen for the latter would be subjective. Thus, we approached from the fact that vegetation was removed and eventually used additional information of elevation, object size and object types. To start with, classification discriminated vegetation and non-vegetation in both Pre_veg and Post_veg in Level 1, which subsequently were combined to create the Level_Change map. It is noted that
using just boundaries of vegetative covered areas to separate mountainous and urban areas intro-
duced some uncertain situations along the boundaries. We observed that buildings were packed into
the areas on the flat terrain and very small vegetation areas were found there. After the earthquake,
small areas of vegetation in the urban area mostly disappeared and temporary houses and tents
were built in the outskirts adjacent to the mountainous areas. To better discriminate landslides and
those small objects, we introduced a further classi-
cification on Level 2 of Pre_veg. After segmenting
the Level_Change, several class-related and object features rules were set to distinguish tents and
landslides classes from change-vegetation reduction class in new level.

For urban areas (Group2), the detection stayed focused in the extensive damages of the buildings
blocks, roads and bridges using the combination of spectral, geometric and texture features and con-
text information. Dealing with lots of detailed information requires a clear hierarchical structure and
rule sets to step-by-step delineate the objects of interest. Such a clear hierarchical structure helps to
break the processing information into smaller sets of information and logically, distributing such
smaller data-sets to different processing units would ease and speed up the process of analysis, iden-
tification and extraction of the damage information. The overall framework is shown in figure 2.

4. Results and discussions

4.1. Original image classification

As shown in figure 3(a), the study area was largely covered by vegetation both sides of the river and
the small town in the middle of the area. For the purpose of splitting and distributing images into
mountainous areas and urban areas, large-scale parameter (250) was adopted to segment image
objects with large pieces. The shape parameter was set to 0.1 in order to give less weight to shape and more weight to spectral information for image segmentation. Besides, the compactness parameter and smoothness were set to 0.5 aiming to equally balance compactness and smoothness of objects. It paid more attention to vegetation and non-vegetation rather than details like trees or single buildings, as shown in figure 3(b). Vegetation was simply separated from non-vegetation by NDVI, which helped to clearly distinguish the urban areas and mountainous areas. Several small isolated vegetation objects in urban areas were filtered out to derive the complete mask for splitting and distributing. Classification result is presented in figure 3(c).

4.2. Group1

4.2.1. Vegetation change detection

After splitting the original images, Pre_veg was first segmented with optimal parameters (scale = 60) via several trial and errors. The segmentation of Level1 was not enough in this scale for the separation of trees and grass, but optimal for separating non-vegetation and vegetation. As mentioned before, the shape parameter was set to 0.1 and the compactness parameter and smoothness were set to 0.5. Likewise, Post_veg segmentation parameters were kept the same as the Pre_veg segmentation. Soil Adjusted Vegetation Index (SAVI), a modification of NDVI, was chosen to classify both Pre_veg and Post_veg images. It could correct for the influence of soil brightness when vegetative cover is low. Pre_veg classification result is shown in figure 4(a), red for non-vegetation (SAVI ≤ 0.72) and green for vegetation (SAVI > 0.72). Classification result of Post_veg is presented in figure 4(b), yellow for non-vegetation (SAVI ≤ 0.43) and green for vegetation (SAVI > 0.43). The non-vegetation class included landslides and bare land.

Figure 4(c) shows the Level_Change map generated from the comparison of Pre_veg and Post_veg in Level 1. Red, vegetation reduction, was the most change part. Light green, vegetation addition, was the areas which vegetation was expanded. Dark green was for vegetation no change, while yellow was for non-vegetation no change. However, parts of change detection classification were misclassified due to the error in Post_veg classification.

4.2.2. Small objects detection with Pre_veg classification in Level 2

We segmented only the vegetation class derived from Level 1 with scale 40 to delineate smaller objects on Level 2. Arable land was segmented into regular shapes and trees with big canopies were separated individually. However, the scale used for this segmentation was not sufficient for
separation of small and low trees mixed with surrounding grass. Further segmentation and classification were employed to clarify this.

From the segmented image, we classify into two classes: pre-tree and pre-grass using Support Vector Machine (SVM) classification (Cortes & Vapnik 1995). Contrast split segmentation is able to isolate trees with higher accuracy after SVM from Pre-Grass class, and also correct some small and misclassified trees. Because the segmentation of trees was a bit trivial, several steps were taken to remove and reshape the small trees, including chessboard segmentation, relations to neighbour objects in class-related features and other object feature rules. Morphological filtering was also used as shape and size filter to obtain a better accuracy. Final classification of pre-tree and pre-grass is shown in [figure 5(a)]. As seen, there are three places marked by blue circles in the zoom-in view. The areas in these circles are gentler, which were probable and suitable to place temporary houses or tents.

The initial segmentation of change map was processed to classify the tents and landslides. The scale was set 20 because the size of tents was smaller than vegetation and common buildings. Small and regular tents were separated from other objects. The roof of tents had higher brightness, which was a significant difference with the surrounding surface features, for example, to separate from landslides class. Brightness value greater than or equal to 405 was set to the Change-Tents class,

![Figure 4](image1.png)

Figure 4. Change detection classification. To view this figure in colour, see the online version of the journal.

![Figure 5](image2.png)

Figure 5. Detection of landslides and tents. To view this figure in colour, see the online version of the journal.
whereas Change-Landslide class was set to smaller than 405. However, there still remained some misclassifications in the Change-Tents class due to their spectral similarity with some landslide spots. The difference between red (R) band and near-infrared (NIR) band was created as customized feature to remove some misclassifications. Besides, from the standpoint of shape, Compactness was taken into consideration. Area (size) was finally used to remove the remaining misclassification. Tents class is shown in bright blue in figure 5(b), and landslides class in pink. It can be seen that pink areas are quite large, occupied more than half vegetation. And tents, within the dark blue circle, concentrated around the villages. Figure 5(c) presents 30-m-resolution DEM including contours and their values. The value of DEM was from 851 to 1375. In the enlarged image, it could be seen clearly the blocks of tents and temporary houses most of which were well identified and extracted. The tents were built on the relatively flat areas, the value of DEM from 870 to 970 under black rectangular, surrounding the village.

To assess the accuracy of our detection, we exploited independent assessment from Virtual Disaster Viewer (VDV) archived at http://vdv.mceer.buffalo.edu/vdv. In responding to large-scale disaster, especially earthquake, an international consortium is established and received damage assessment, field observation contributed from all members. Figure 6 shows the comparison of our detected result and that of VDV. Except the missing part in the southern area from VDV, both results look similar. Taking 50 random points, the accuracy is computed as presented in table 1. Overall, we achieved an acceptable accuracy of 72% employing a simple and fast approach. Importantly, the other process working with complex urban areas does not need to concern about this large area of mountainous area.

Table 1. Landslide accuracy assessment.

| True positive = 31 | False positive = 13 |
|-------------------|--------------------|
| False negative = 1 | True negative = 5 |
| Accuracy = (31 + 5)/(31 + 5 + 13 + 1) = 72% |
| True positive rate = 31/(31 + 1) = 96.8% |
| True negative rate = 5/(5 + 13) = 27.7% |

Figure 6. Landslide detected results (a) in comparison with VDV data (b).
4.3. Group2

In the urban areas, shadow was more distinctive with lower brightness from other objects, like surrounding rivers, intact buildings or trees. So it was classified and extracted first in Level 1. Segmentation scale was set to 20, in order to separate shadow from buildings, trees, bridges and roads along the shore. Most of buildings were damaged and collapsed after the disaster, thus only two shadow objects were extracted. Temporary houses and tents were too low, and hence no obvious shadow. The trees casting the shadow were mostly big and single rather than the flocks of trees. Not all river embankments were extracted, and some were damaged and covered by landslides. Only the shadow of big bridge at the river junction was extracted completely.

The hierarchical segmentation scale in Level 2, set to 25, was created on top of Level 1 with the mask of shadow class. Vegetation was chosen as the second class because it was easier extracted than others in such complex features of the urban. SAVI and ratio were used in the first step of extraction. Due to the obvious difference between vegetation homogeneity textures with other features, Gray-Level Co-occurrence Matrix (GLCM) Homogeneity was adopted to remove some misclassified objects. It could be seen that almost all vegetation was classified, including single trees along the river.

In Level 3, the segmentation scale of water was equal to 30, which was created above Level 2 using hierarchical segmentation again. Shadow and vegetation classes were masked out. The result of water segmentation was fragmented and smashed into pieces. NDWI was used to extract water and because of water obvious shape characteristic, Asymmetry (shape properties) was also adopted to extract water. After merging the water objects, Area was employed to eliminate a small amount of misclassifications.

According to hierarchical segmentation and classification, the scale of roads and bridges was set to 40 in Level 4, created above Level 3 and masked out formerly detected classes. Bridges were segmented into regular shape, and the significant difference of roads and bridges from others was shape property. Their spectral reflectance was a little lower in comparison with the surroundings, hence GLCM mean was adopted to eliminate some misclassified objects. Since bridges were separated well from water even the narrowest bridge in Level 3, all bridges were extracted. It was obvious that most of the roads were extracted in pieces, not well connected, except some main roads. The reason was that some big trees were along with roads, and covered partially or completely. On the other hand, no roads were extracted in village areas due to the heavy damages.

In Level 5, the segmentation scale was set to 30, newly created from pixel level. Temporary houses and intact buildings classes were separated well and in relatively regular shape from remaining objects. It was easy to find that the roof of the temporary houses had a distinctive colour: blue. So the difference between red and blue band was chosen to extract the temporary houses. After merging temporary houses objects, area and mean values were used to remove small misclassifications. GLCM mean measure was employed to extract shallow along the water. To avoid misclassification, based on the context with the water, border to water was adopted with Area after merging shallow objects. Nevertheless, some areas were covered by gravel due to the earthquake and landslides.

The tents were in the range 427–624 of brightness. Most tents were arranged in a straight order. To remove a small amount of misclassification, shape index was first adopted because of its regular shape. Second, based on the spectral characteristics, mean value and standard deviation were both used to separate from the surrounding objects. Third, GLCM homogeneity was used to remove the remaining misclassifications. Because few tents were placed into curved shapes and the brightness of those was quite low and easy to mix with surrounding debris, we failed to identify and extract them.

Through visual interpretation, the roof of intact buildings was in rectangular shape. So rectangular fit was used to extract the intact buildings and area was used to remove larger objects. Besides, the spectral characteristics, such like brightness and ratio, were also used to avoid misclassification. To separate from surrounding collapsed areas, GLCM dissimilar was chosen to eliminate the
remaining misclassified objects. However, the misclassification existed because trees could cover partial or complete buildings. Usually visual interpretation is the only way to deal with such cases.

The final urban damage mapping of our detected results of intact buildings, infrastructures, tents, vegetation, water and collapse area is presented in details in figure 7(a). The identification of shadow, vegetation, water, temporary houses, tents and shallow was reasonably good. However, the identification of roads and bridges class was found to be very complex. Our detected ‘collapse’ areas are corresponding to the areas of heavily damaged buildings and infrastructures. We also used VDV data as references for accuracy assessment here. On VDV, damages were categorized to slight/no damage, extensive damage, collapse and indistinguishable. Leaving out the indistinguishable points, we interpreted slight/no damage as our intact buildings, and the other two categories as our collapse category. We can observe the good match between our detected collapse areas and the red (damaged) points visually. The detected results also proved to be good quantitatively as shown in table 2 using 50 random samples. The final set of rules applied in this case study was chosen to work appropriately for the study area but applicable to other study areas. Though it would be scrutinized for an optimal result, in the context of post-disaster when time is critical, the established rules are acceptable.

**Table 2.** Damaged building accuracy assessment.

|               | True positive | False positive | False negative | True negative |
|---------------|---------------|----------------|----------------|--------------|
| True positive | 37            | 6              | 3              | 4            |
| Accuracy      | \(\frac{(37 + 4)}{(37 + 3 + 6 + 4)} = 82\%\) | \(37 / (37 + 3) = 92.5\%\) | \(4 / (6 + 4) = 40\%\) |
5. Conclusions

We presented the implementation of the distributed and hierarchical object-based analysis approach to detect the damages in YingXiu town caused by the 2008 Wenchuan earthquake. The distributed OBIA approach promoted the processing speed and reduced the hardware configuration in the study with splitting the entire original images into sub images. Two or more computers could be used in parallel to process and analyze these sub-images based on different requirements. In this study, the outcomes were produced at an acceptable accuracy.

In the mountainous areas, by monitoring the change of vegetation, we could extract the landslides areas rapidly with very good overall accuracies. The hierarchical framework proved to be an optimal classification process to quickly and effectively extract the damage information. Landslide detection achieved 72% whereas damaged building detection achieved 82% overall accuracy in comparison with independent damage assessment provided on VDV platform. The classification rules based on fuzzy membership functions are applicable in similar situations. The detailed detected information is valuable in search and rescue operations, and for planning for recovery and reconstruction after earthquakes as well. Other ancillary data, such as LIDAR, thematic map and high-resolution DEM will be used to improve the classification of roads and buildings. In addition, more experiments with other data-sets such as that of other areas in Wenchuan, the 2011 Japan earthquake or the 2015 Nepal earthquake, will be carried out to test the transferability and applicability of the eCognition protocols developed in this study.

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Disclosure statement

No potential conflict of interest was reported by the authors.

Notes on contributors

Jing Sun is an educated master student of geodesy and geoinformatics at Royal Institute of Technology, KTH. She is interested in analyzing and processing remote sensing images in disaster management and recovery. Her research currently focuses on generate more effective and automatic approaches using in search and rescue operations in disaster areas.

Dr Tuong-Thuy Vu is an associate professor and head of OSGEO research lab at the School of Geography, University of Nottingham, Malaysia campus. He is leading a research team working on big geospatial data analytics and high-performance computing. Currently, his team focuses on remote sensing image analysis service and application to disaster management.

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