DETECTION OF LANDSLIDE AREAS USING UNSUPERVISED CHANGE DETECTION WITH HIGH-RESOLUTION REMOTE SENSING IMAGES

No-Wook Park and Kwang-Hoon Chi

Geoscience Information Center, Korea Institute of Geoscience and Mineral Resources
30 Gajeong-dong, Yuseong-gu, Daejeon 305-350, Korea
nwpark@kigam.re.kr

ABSTRACT:

This paper presents an unsupervised change detection methodology designed for the detection of landslide areas. The proposed methodology consists of two analytical steps: one for multi-temporal segmentation and the other for automatic selection of thresholding values. By considering the conditions of landslide occurrences and the spectral behavior of multi-temporal remote sensing images, some specific procedures are included in the analytical steps mentioned above. The effectiveness and applicability of the methodology proposed here were illustrated by a case study of the Gangneung area, Korea. The case study demonstrated that the proposed methodology could detect about 83% of landslide occurrences.

KEY WORDS: Change Detection, Landslides, Object, Thresholding

1. INTRODUCTION

For landslide hazard mapping, any analytical models are based on quantitative relationships between landslide areas and input spatial data sets. To derive those relationships, it is very important to detect past landslide areas. Since most landslides occur in mountain areas, traditional field survey has various limitations such as inaccessibility and much cost. Meanwhile, remote sensing data can consistently provide periodic and regional information and the landslide areas can be detected by using multi-temporal data before and after landslide occurrences. Recently available high-resolution data (e.g. pixel resolution of 1m or less) such IKONOS, QuickBird and KOMPSAT-2 can be used to detect landslides occurred on a small scale.

This paper presents an unsupervised change detection approach to detect past landslides using high-resolution remote sensing data. The methodology is based on object-based multi-temporal segmentation and automatic determination of thresholding values for unsupervised change detection. To reduce noisy effects in traditional pixel-based traditional change detection, image objects are first extracted from multi-temporal data and then change vector analysis is applied within each object. Instead of the empirical trial-and-error procedure for the selection of the threshold value between changed and unchanged pixels, an automatic selection of the threshold values based on Gaussian mixtures and an expectation-maximization (EM) algorithm is applied. The proposed scheme was validated from the case study of the Gangneung area, Korea where many landslides were triggered by typhoon RUSA in 2002.

2. APPLIED METHODOLOGY

2.1 Study Area and Data

The study area had serious landslide damage as a result of typhoon RUSA aftermath and heavy rainfall early in September, 2002. The landslides triggered by intense rainfall resulted in both extensive damage to property and the loss of lives.

To detect the locations of the landslides, two high-resolution remote sensing images (i.e. IKONOS and QuickBird acquired on 14 October, 2001 and 20 July, 2003, respectively) were used for change detection analysis.

2.2 Analytical Procedure

Before change detection analysis, several pre-processing methods were applied to the data set. If panchromatic data are only used for analysis, it has limitations to reveal the characteristics of landslide areas due to one band with broad spectral ranges. To overcome the limitations, the pixel level fusion of panchromatic and multi-spectral data was carried out. To reduce the spectral discrepancy caused by differences in acquisition dates, radiometric normalization using multivariate regression with pseudo invariant sets was also carried out. Pre-processed 4 bands with a pixel resolution of 1m were used as inputs of a change detection system.

Most landslides are represented spatially as one object consisting of scarp and deposit areas. If the traditional pixel-based analysis is applied, the analysis may show very noisy detection results. Sometimes, the scarp and deposit areas are separated and as a result, two landslide areas may be detected as if they were different landslides.

To consider above limitations of pixel-based analysis, object-based change detection analysis was applied. Figure 1 shows a change detection procedure applied in this study.

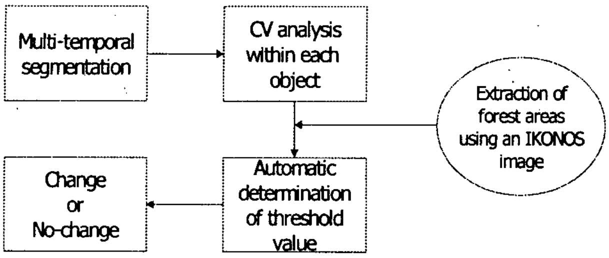

Figure 1. Unsupervised change detection work flow.

First, multi-temporal objects by using multi-temporal images were extracted. For object extraction, object-based segmentation by using spectral and spatial information was applied by using the eCognition software. By multi-temporal object segmentation, landslide areas are expressed in one object and spectral information before and after occurrences will be included within the object. Within those objects, change vector analysis was applied to obtain quantitative change extent.

In unsupervised change detection analysis, the amount of information on change or non-change is obtained to apply thresholding values that discriminate the change areas from unchanged ones. However, the traditional approach cannot be directly applied to the study area, since it contains cultivated zones and thus their conditions are quite different due to differences in acquisition dates. In this case, the one thresholding value cannot properly discriminate the changed areas from unchanged ones. Considering these conditions, forest areas were extracted from IKONOS acquired before the landslide occurred. Then change detection analysis was applied to those forest areas, under the assumption that landslides in the study area occurred in the forest areas. Thus, the changed areas would include landslides and newly constructed or destroyed facilities.

To select a proper thresholding value, the automatic selection method (Bruzzone and Prieto, 2000; Park et al., 2003) was applied. It assumes that the change vector or difference image can be modelled as Gaussian mixtures. The model parameters for Gaussian mixtures are estimated by applying the EM algorithm that iteratively modifies the parameters to maximize the likelihood of the data. After determining the model parameters using the EM algorithm, the threshold values are finally determined using the Bayesian rule for minimum error.

3. RESULTS AND DISCUSSION

Figure 2 shows the multi-temporal segmentation result in some areas. As shown in Figure 2, landslide areas including scarp and deposit areas are expressed as the objects and their spectral information is discriminated from surrounding areas.

Figure 2. Multi-temporal segmentation result. Three areas highlighted by circles are actual landslide areas.

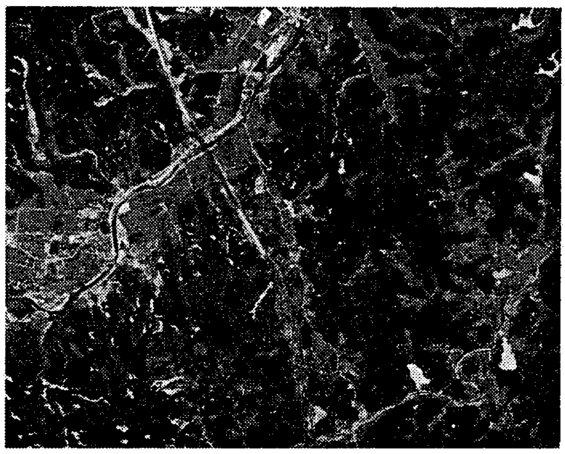

Figure 3. Change detection results. Changed objects and actual landslide locations are denoted as yellow and blue colors, respectively. The background image is QuickBird acquired after landslide occurrences.

The final change detection results and actual landslide locations are shown in Figure 3. The actual landslide locations were verified by field survey. Figure 4 shows some enlarged areas for visual comparison of changed areas, multi-temporal segmentation and field photo.

Figure 4. Comparison of changed areas and field photo.

The number of changed objects was 270. As a result of the field survey and visual interpretation, the changed objects included landslides, construction sites, newly generated forest roads and tombs and misclassified forest areas. The number of actual landslide areas was 282. The smaller number of changed objects than that of the actual landslide areas is due to the fact that several small neighbouring landslides were expressed as one object. The number of missed landslides was 49 and landslide detection rate about 83%. The missed alarm can be attributed by a few reasons. The first possible explanation is that the scale parameter in object segmentation (in our case, 50) could not represent small landslides. There is a strong possibility that several landslides have occurred in very steep areas. Despite the high spatial resolution of IKONOS and QuickBird images, it was very difficult to identify some objects in very steep areas due to two dimensional projection or imaging of three dimensional actual objects.

4. CONCLUSIONS

To automatically detect the landslide areas, this paper presented and applied unsupervised change detection analysis based on multi-temporal object segmentation and automatic selection of thresholding values. From the case study, the proposed methodology detected about 83% of actual landslide areas. These results would confirm that the methodology can be effectively applied to the detection of landslide areas or other changed objects. To refine the proposed methodology and case study results, the incorporation of other information (e.g. slope or elevation) into the proposed methodology will be considered.

5. REFERENCES

Bruzzone, L. and D.F. Prieto, 2000. Automatic analysis of the difference image for unsupervised change detection. *IEEE Transactions on Geoscience and Remote Sensing*, 38(3), pp. 1171-1182.

Park, N.-W., K.-H. Chi, K.-J. Lee, and B.-D. Kwon, 2003. Automatic estimation of threshold values for change detection of multi-temporal remote sensing images. *Korean Journal of Remote Sensing*, 19(6), pp. 465-478.

6. ACKNOWLEDGEMENTS

This work was supported by a grant from the Korean Ministry of Science and Technology (MOST). The authors would like to express a sincere appreciation to the MOST.