USING OBJECT-BASED CLASSIFICATION TO DETECT LANDSLIDES SITES USING HIGH RESOLUTION AERIAL IMAGES

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Abstract:A variety of image classification methods have been applied in satellite images analysis, including supervised, unsupervised, and hybrid classifications. However, many researches indicated that traditional pixel-based classification approaches often resulted in less satisfactory outcome when applied to high resolution aerial image data. The main reason is that pixel-based approaches often raise over-classification problem as the spatial resolution of images increases. The objective of this study is to use object-based classification method to detect landslides sites in aerial images acquired by Z/I DMC and Leica ADS40. Firstly, multiresolutionsegmentation technique will be applied to segment image into regions that correspond to various areas of interest. Then each region will be classified into appropriate land cover types by using different kinds of indexes which are defined in this study, and the landslide sites will be identified. Finally, the result of landslides sites can show that the object-based classification is a good method for extracting the areas of landslides.

1. INTRODUCTION

Traditional image classification methods, including supervised classification, unsupervised classification and hybrid classification, use per-pixel information to analyze human-made structures or natural objects. With the progress on the techniques of sensors equipped on aircraft or satellite, the spatial resolutions of remote sensing data can reach at $\leq 1\times 1$ m, such as WorldView-2 (0.46×0.46 m of panchromatic band) and Z/I DMC (0.25×0.25 m in this study). Therefore, it is difficult to classify high resolution remote sensing data based on the spectral characteristics of a single pixel, which probably is noise or outlier in the data. Furthermore, the noises in images often cause problems to image classification called salt-and-pepper effect (Jensen, 2005).

To overcome the problem of salt-and-pepper effect, object-based classification method was proposed for high resolution remote sensing data. This concept of object-based classification, which is based on image segmentation, and the result is the creation of image objects defined as individual areas with shapes and spectral homogeneity (Benz, 2001), has been implemented since the early 1970s (De Kok et al, 1999). However, it was difficult to use this method because of lacking of computer power. Until 1990s, the power of computer has improved so that this method (object-based) can be used in high spatial resolution images (Franklin et al, 2003).The object-based classification has become popular in recently years, and this method is superior to pixel-based classification. For example, Whiteside and Ahmad (2005) compared object-based with pixel-based classification of land cover objects in Northern Australia, and this result showed that the accuracy of classification was better by using object-basedmethod (78% accuracy) than pixel-based (69.1% accuracy). Moreover, Platt and Rapoza (2008) used object-based classification method to identify several land cover objects, and they integrated the expert knowledge (rules of image classification) to improve the accuracy of land cover classification.

Therefore, the objective of this study was to use object-based method for extracting the landslides sites in aerial images, and this study carried out by usingeCognition software. First, this study used multiresolution technique to segment images into individual region. Next, there are three different types of indexes, which are Spectral Reflectance,Shape & Extent and Geological indexes, using in this study to establish classification rules of detecting landslides sites. Finally, this study did not only use raster data, but also used vector data to improve the accuracy of extracting landslides sites.

2. SEGMENTATIONALGORITHM ANDINDEXS

2.1 Multiresolution Segmentation Algorithm

The multiresolution segmentation algorithm, which is a bottom-up segmentation algorithm, can continuous merge pixels or image objects, and the steps of this segmentation algorithm is as follows(eCognition 8.7.2 reference book):

Step 1: Randomly select the initial seeds of an Image, and each seed finds its best-fitting neighbor.
Step 2: Update the initial seed to its neighbor if it cannot find its best-fitting neighbor.
Step 3: Merge an image object until the initial seed find its best-fitting neighbor.
Step 4: Repeat Step 2 and Step 3 until there is no image objects which is necessary to be merged.

2.2 Spectral Reflectance Index

The spectral reflectance indexes used in this study are brightness and NDVI (Normalized Difference Vegetation Index), and these indexes are introduced as follows:

2.2.1 Brightness: The index of Brightness shows the spectral reflectance intensity of an image, and the equation is as follows(eCognition 8.7.2 reference book):

$$\bar{C}(V) = {}^{1}\!/_{W^{B}} \sum_{k=1}^{k} W_k^B \, \overline{C_k}(V)$$

Where K = the number of image bands
$\bar{C}(V)$ = the Brightness of an image
$\overline{C_k}(V)$ = the mean intensity of image band k
W_k^B = the brightness weight of image band k
W^B = the sum of W_k^B

2.2.2 NDVI: The index of NDVI can detect the area of live green plants. The reason is that the near-infrared band (the bandwidth of this band range from 0.76 to 0.90 μm)is very responsive to the amount of vegetation area (Jensen, 2007). The equation is as follows:

$$\mathrm{NDVI} = \frac{\mathrm{IR} - \mathrm{R}}{\mathrm{IR} + \mathrm{R}}$$

Where IR = the near-infrared band whose bandwidth is between 0.76 to 0.90μm

R = the red band whose bandwidth is between 0.63 to 0.69μm

2.3 Shape and Extent Index

The shape indexes, which are used to describe the shape information of each segmented region (image object), are Rectangular Fit and the ratio of Length/Width, and the area of each segmented region is the extent index used in this study.

2.3.1 Rectangular Fit: The index of Rectangular Fit can describehow well an image object fits into a rectangle of similar size and proportions. If the value is 0, it indicates that the image object is not fit into a rectangle, and the value 1 indicates that this object is complete fitting into a rectangle(eCognition 8.7.2 reference book).

2.3.2 Length/Width: The index is to calculate the ratio of length/width in each image object, and its length and width is calculated by pixel number(eCognition 8.7.2 reference book).

2.3.3 Area: The index is to calculate the area of each image object by pixel number.

2.4 Geological Index

The Geological indexes used in this study are slope, collapse direction which was defined in this study, and river overlap area. First two indexes (slope and collapse) are derived from DEM (Digital Elevation Model) data, and the third index (river overlap area).

2.4.1 Slope: Theslope index is the rates of change of the surface in the horizontal and vertical direction from the center cell. The basic equation is as follows:

$$\text{Slope} = \tan^{-1} \sqrt[2]{({dz}/{dx})^2 + ({dz}/{dy})^2}$$

Where${dz}/{dx}$ = the horizontal direction from center cell
${dz}/{dy}$= the vertical direction from center cell

2.4.2 Collapse Direction: The collapse direction defined in this study is used two indexes: main direction and aspect. The definition of main direction is based on the direction of largest eigenvector, and the equation is as follows and shown in Figure 1.

$$\text{Main Direction} = {180°}/{\pi} \tan^{-1}(VarXY, \lambda_1 - VarY) + 90°$$

Where VarX = the variance of X
VarY = the variance of Y
λ_1 = the eigenvalue

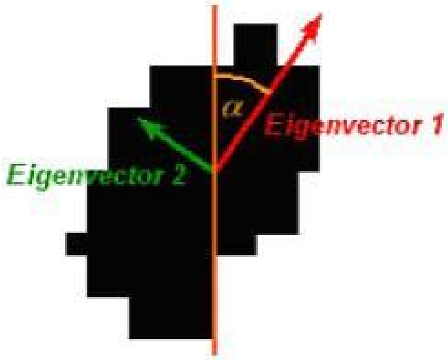

Figure 1: The main direction of an image object (eCognition 8.7.2 reference book)

The other index used to calculate the collapse direction is aspect, and this index whose equation is as follows and shown in Figure 2 can identify the downslope direction of the maximum rate of change in value from each cell to its neighbors.

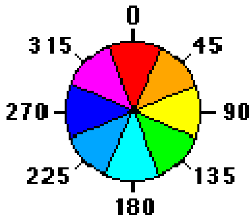

Figure2: The direction of aspect (ArcGIS 10.0 help documentation)

a	b	c
d	e	f
g	h	i

Figure3: The algorithm of aspect (ArcGIS 10.0 help documentation)

From Figure 3, the basic step of aspect is as follows (ArcGIS 10.0 help documentation):

Step 1: Calculate the rate of change in the x direction for cell e (Figure 3).

$$^{dz}/_{dx} = ((c + 2f + i) - (a + 2d + g))/8$$

Where z = the elevation of an image object
x = the x direction of an image object

Step 2: Calculate the rate of change in the y direction for cell e (Figure 3).

$$^{dz}/_{dy} = ((g + 2h + i) - (a + 2b + c))/8$$

Where z = the elevation of an image object
y = the y direction of an image object

Step 3: Calculate the aspect using the rate of change in both the x and y direction.

$$\text{Aspect} = {}^{180°}/_{\pi} * atan2({}^{dz}/_{dy}, {}^{-dz}/_{dx})$$

Where z = the elevation of an image object
x = the x direction of an image object
y = the y direction of an image object

The collapse direction is calculated by absolute value of difference between main direction and aspect, and this equation is as follows:

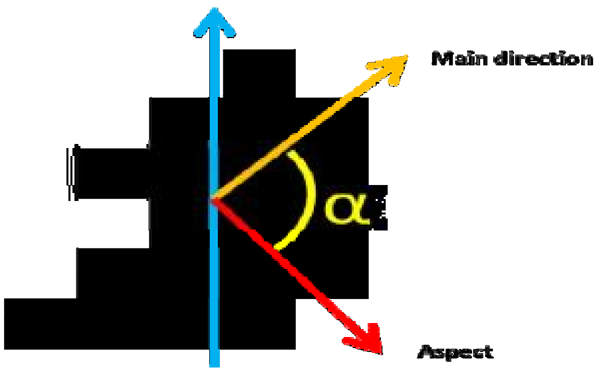

Figure 4: The collapse direction of an image object

$$\text{Collapse direction} = \text{abs}(\text{Main direction} - \text{Aspect}) \text{ or } 360° - \text{abs}(\text{Main direction} - \text{Aspect})$$

2.4.3 River Overlap Area: The index is to look for the areas which are overlapped by river data.

3. EXPERIMENTS AND DISCUSSUIN

This study usedthree parts of indexes, which are includingspectral reflectance indexes, shape and extent indexes, and Geological indexesintroduced on Section 2. In this study, the thresholds of each index are illustrated as Table 1, and these thresholds are calculated by try and error method.

Table 1: The information of each index

Index	Threshold (Try and Error)	Applied Area	Figure
Brightness	> =23000	Find possible landslide area	Figure 6
NDVI	<= -0.05	Remove non-vegetation area	Figure 7
Rectangular Fit	>= 0.85	Find human-made area	Figure 8
Length/Width	> =3.2	Find long-narrow area	Figure 9
Area	<= 150 (pixel number)	Find small area	Figure 10
Slope	< =10 (degree)	Find flat area	Figure 11
Collapse Direction	<= 45 (degree)	Find possible landslide area	Figure 12
River Overlap Area	>= 1 (overlap number)	Find area which is overlapped by river area	Figure 13

The extraction results by usingspectral reflectance indexes, which are including brightness and NDVI, are shown from Figure 6 to Figure 7.It is shown that the brightness in vegetation area is not as stronger as other feature objects such as landslides and rivers, but the NDVI of vegetation is larger than other feature objects. Therefore, using brightness index and NDVI index can remove vegetation areas easily.

Figure5: Raw Image

Figure6: Brightness

Figure7: NDVI

The extraction results by using shape and extent indexes, which are including Rectangular Fit, Length/Width, and Area, are illustrated from Figure 8 to Figure 10.It is useful to remove human-made feature objects by using Rectangular Fit index. For example, the shape of buildings and paddiesis similar to rectangle. The second index of shape used in this study is Length/Width, and using this index can remove some non-landslide areas, such as roads and river edges. In addition, this study uses Area index to remove small objects, which is not the areas of landslides.

Figure 8: Rectangular Fit

Figure9: Length/Width

Figure 10: Area

As illustrated from Figure 11 to Figure 13, there are three Geological indexes, which are including Slope, Collapse Direction and River Overlap Area. Using Slope index, whose spectral reflectance indexes and shape & extent indexes are similar to landslides areas, can recognizethe non-landslides areas, for the slope of these areas are lower than the areas of landslides.The second index of Geological indexes is Collapse Direction, and this index can remove the river edge areas. Moreover, the River Overlap Area index can show the areas of river sediments, and it is important to identify whether these areas are landslides areas or not.

Figure 11: Slope

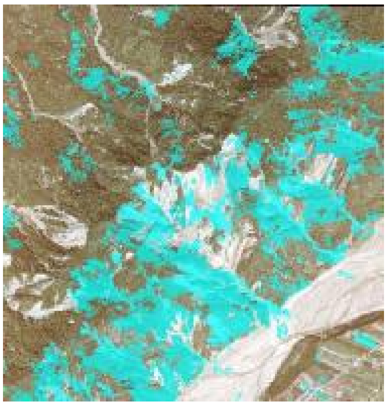

Figure12: Collapse Direction

Figure13: River Overlap Area

The results of this study are illustrated from Figure 14 to Figure 16.The initial result is shown in Figure 14, and the rules areconstructed from indexes shown in Table 1, including Area, Brightness, Slope, NDVI and Rectangular Fit.However, there are still misclassifiedregions of landslides, such as river edge areas shown in red circles of Figure 14. To deal with the problem, this study uses the Length/Width index and Collapse Direction index to detect the river edge areas. If the Length/Width value of an image object is larger than the threshold and the Collapse Direction value is smaller than the threshold, this image object may be the river edge area shown in Figure 15.

Moreover, because some extracted regions of landslides may be the sediments by rivers, this study uses river vector data to extract the landslides areas which is overlapped by rivers. Thus, the final landslides areas result are illustrated as Figure 16, and the image objects with blue color are rivers, with orange color are landslides, and with yellow color are river sediments.


Figure 14: Misclassified landslides


Figure 15: River edge areas


Figure 16: Final landslide areas

4. CONCLUSIONS AND RECOMMENDATIONS

This study used object-based classification to extract the landslides sites in aerial images, and this method is different from the pixel-based classification. Unlike the pixel-based classification, the object-based classification implementsimage segmentation firstly, and then implements classification based on each segmented region,which is also regarded as individual image object. In addition, there are three kinds of indexes, which are Spectral Reflectance, Shape & Extent and Geological, using in this study, and these indexes can improve the accuracy of extracting landslides areas. For example, using Spectral Reflectance indexes, such as NDVI, will remove the most of vegetation areas, and using Shape & Extent indexes can identify whether the image objects are human-made or not. Moreover, it is helpful to use Geological indexes, such as Slope and Collapse Direction,for detecting the river sediments, whose Spectral Reflectance and Shape & Extent indexes are similar to landslides sites. Besides using raster data (aerial images, DEM, and Slope) to extract the areas of landslides, this study also used vector data (river layers shapefile data) to enhance the accuracy of detecting landslides sites.

Although there are several advantages using different kinds of indexes to extract the landslides areas in this study, it is still existingtwoproblems in this study. The first is how to decide the thresholds of each index,and the second is what kinds of data can be used to extract the areas of landslides.At the first problem, this study uses try and error method to identify the thresholds of each index, but this method is not as good as using statistic measurement. Therefore, it is recommended that using statistic measurement to identify the thresholds of each index. At the second problem, it is suggested that using LiDAR (Light Detection And Ranging) data, which can give the more accuracy information of surface, but it is not used in this study.

REFERENCES:

Benz, U., 2001. Definiens Imaging Gmbh: Object-oriented classification and feature dection. IEEE Geoscience and Remote Sensing Society Newsletter, pp.16-20.
De Kok, R., T. Schneider, and U. Ammer, 1999.Object-based classification and applications in theAlpine forest environment. In: Proc. Joint ISPRS/EARSelWorkship, “Fusion of sensor data, knowledge sources and algorithms”, Valladolid,Spain, 3-4 June, 1999.
Definiens AG,2012.DefinienseCognition Developer 8.7.2 – Reference Book.
Franklin, J., Phinn, S. R., Woodcock, C.E. and Rogan, J,2003. Rationale and conceptual framework for classification approaches to assess forest resources and properties. In M. Wulder and S. Franklin (Ed.), Methods and Applications for Remote Sensing of Forests: Concepts and Case Studies 1 ed. pp. 279-300, Boston: Kluwer Academic Publishers
Whiteside, T., and W. Ahmad. 2005. A comparisonof object-oriented and pixel-based classificationmethods for mapping land cover in northernAustralia. In: Proceedings of SSC2005 Spatial intelligence,innovation and praxis: The National BiennialConference of the Spatial Sciences Institute, pp. 1225–1231,Melbourne, Australia: Spatial Sciences Institute.
Jensen, J.R, 2007.Remote Sensing of the Environment, Pearson Eductation.
Jensen, J.R, 2005.Introductory Digital Image Processing, Pearson Eductation.
Platt, R. V., and A. F. H. Goetz, 2004. A comparisonof AVIRIS and synthetic Landsat data for land useclassification at the urban fringe. PhotogrammetricEngineering and Remote Sensing, pp.813–819.