OPTIMIZED IMAGE SEGMENTATION AND ITS EFFECT ON CLASSIFICATION ACCURACY

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ABSTRACT:

Image segmentation is a preliminary and critical step in segment-based image analysis. Its proper evaluation ensures that the best segmentation result is used in image classification. In this paper, image segmentations were carried out and the results were evaluated with an objective function that aims at maximizing homogeneity within segments and separability between neighbouring segments. The segmented images were classified with Maximum Likelihood Classifier (MLC) and the classification results were evaluated with independent ground data. The optimal segmentation, i.e. with the highest objective function value, also resulted in the highest classification accuracy, which is 5.92% higher than that obtained by the segmentation with the lower objective function value, and the difference is significant by McNemar's test with p= 0.05, p is the significance level. This shows that the objective function is indeed an effective way to determine the optimal segmentations to carry out the classifications. Pixel-based MLC was also carried out to compare with the segment-based classification. Besides free of salt-and-pepper effect, the best-segmentation-based classification obtained accuracy 2.3% higher than obtained by the pixel-based classification. Though by McNemar's test, the difference is not significance, with p=0.05. This result seems to suggest that the benefit of segmentation-based classification lies not only in the segmentation step, which alone leads to marginal classification improvement, but that the use of segments' shape, contextual as well as spectral information, is needed to increase accuracy significantly.

1. INTRODUCTION

Traditional digital image classification methods do not make use of spatial information in the image and thus are not suited to deal with the inherent heterogeneity within typical land-cover units. Additionally, the resulting thematic maps normally suffer from a salt-and-pepper effect, and lead either to very general land-cover information, or else detailed maps with limited accuracies (Franklin *et al*. 2000, Zhu *et al*. 2000). The development of segment-based analysis stems primarily from the desire to use the important semantic information, which is important to interpret an image and is not presented in single pixels but rather in meaningful segments and their mutual relations. In segment-based classification, homogeneous image segments at a chosen resolution are first extracted and subsequently classified. Since segments are groups of pixels, the spectral related characteristics of segments such as mean, standard deviation etc. can be calculated. More importantly, the segments' shape, texture, and contextual information can be derived and used in image classification (Shackelford 2003). These extra degrees of freedom provided by the segments will aid in image classification.

Image segmentation is a preliminary and critical step in segment based classification, and it is assumed in this paper that segmentation results directly affect the performance of the subsequent classification. One principal point of concern here is the selection of segmentation parameters, which has conventionally been based on trial-and-error approaches (Flanders *et al*. 2003, Giada *et al*. 2003, Gitas *et al*. 2004, Gao *et al*. 2006). Espindola *et al*. (2006) recently proposed an objective function to decide which parameter settings generate the best segmentation results, based on *intrasegment* homogeneity and *intersegment* separability. The method is robust as it utilizes the inherent characteristics of images: variance and spatial autocorrelation, which have not been considered in image segmentation evaluation before (Pal and Pal 1993, Evans *et al*. 2002, Benz 2004). In this paper, image segmentation was performed in SPRING (Câmara *et al*. 1996), which is a non-commercial programme and ranked second in segmentation quality among seven algorithms tested by Meinel and Neubert (2004). This paper assessed the actual benefit of segmentation optimisation by objective function on the resulting classification. Segmented images were classified by MLC to test the hypothesis that the best segmentations also leads to the classifications with the highest accuracy. The ultimate aim of this paper is not so much segmentation optimisation *per se*, but rather to assess its actual benefit on the resulting classification and also to guide future users of SPRING and similar packages in achieving optimal segmentation results that demonstrably lead to improved classification accuracies.

2. STUDY AREA

The study area is located in Michoacan state, central west of Mexico, covering an area of approximately 58*60 km ^{2} , within the longitude of 19° 02’ N and 19° 36’ N, and latitude of 102° 00’ W and 102° 32’ W (figure 1).

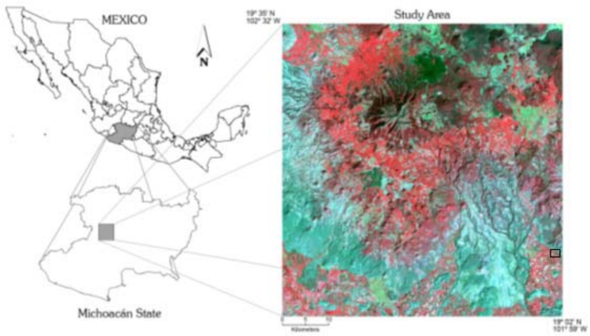


Figure 1. The study area.

3. DATA AND METHODOLOGY

3.1. Data

The available data comprise of a Landsat ETM+ image obtained on 16/Feb/2003 during the dry season, containing 6 bands with a spatial resolution of 30m; a mosaic of 25 ortho-corrected photos taken in 1995 with 2 meters spatial resolution from Instituto Nacional de Estadistica Geografia e Informatica (INEGI), and a land cover map generated from a project “National Forest Inventory of Mexico” in 2000. The satellite image was geometrically corrected by GCPs extracted from the ortho-corrected photographs, with a RMS error (16.5m) well below one pixel (30 m).

3.2. Image segmentation and region growing in SPRING

Image segmentation divides images into continuous and contiguous homogeneous regions. Region growing techniques are being widely used for remote sensing applications and they guarantee creating closed regions (Espanola *et al*. 2006). In region growing, segments are formed starting from suitable initial pixels (seeds) by iteratively augmenting them with neighbouring pixels that satisfy a chosen homogeneity criteria. The process stops when all pixels are segmented into objects. The segmentation algorithm in SPRING uses region growing segmentation method (Câmara *et al*. 1996). It has two parameters, “similarity” and “area”, to guide the segmentation procedure. “Similarity” is a threshold value that determines if two neighbouring pixels (objects) are grouped, while the “area” threshold is used to filter out the objects smaller than this value. The segmentation quality was evaluated with an objective function proposed by Espindola *et al.* (2006). The objective function combines the variance measure and the autocorrelation measure given by equation 1:

$$F(v,I) = F(v) + F(I) \qquad (1)$$

In which Function $F(v)$ and $F(I)$ are normalized functions. The calculation of variance is give by:

$$v = \frac{\sum_{i=1}^{i} a_i . v_i}{\sum_{i=1}^{n} a_i} \qquad (2)$$

where v_i is the variance of a segment and a_i is its area; the calculation of Moran’s I is expressed as:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - y)(y_j - y)}{(\sum_{i=1}^{n}(y_i - y)^2)(\sum_{i \neq j}\sum w_{ij})} \qquad (3)$$

where *n* is the total number of regions, w_{ij} is a measure of the spatial proximity, y_i is the mean grey value of region R_i , and y is the mean grey value of the image. Each weight w_{ij} is a measure of the spatial adjacency of regions R_i and R_j . If regions R_i and R_j are adjacent, w_{ij} = 1. Otherwise, w_{ij} = 0. The description of objective function is in Espindola *et al*. 2006.

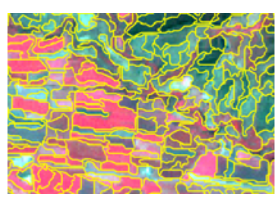
3.3. Segmentation-based classification, accuracy assessment, and McNemar’s test

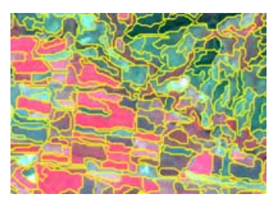
MLC was applied to allocate segments into land cover types. Classification accuracy was evaluated with ground data interpreted from orthophotos, the land cover map and with ground survey data, comprising 305 random points. Error matrices were generated. McNemar’s test was used to evaluate the significance in the difference of the classification accuracy (Foody 2004).

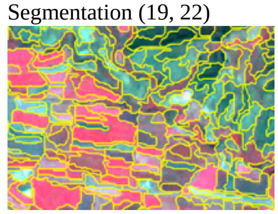
4. RESULTS AND DISCUSSIONS

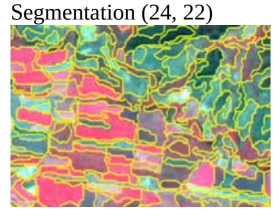
4.1. Image segmentation results

Ten segmentations were generated with various parameter settings (Figure 2), with similarity thresholds ranging from 19 to 64 in intervals of 5, and an area threshold of a constant 22 in accordance with recommendations by Espindola *et al.* (2006) who also used a Landsat image and found optimal segmentation results with this “area” threshold.


Segmentation (19, 22)


Segmentation (24, 22)


Segmentation (29, 22)


Segmentation (34, 22)

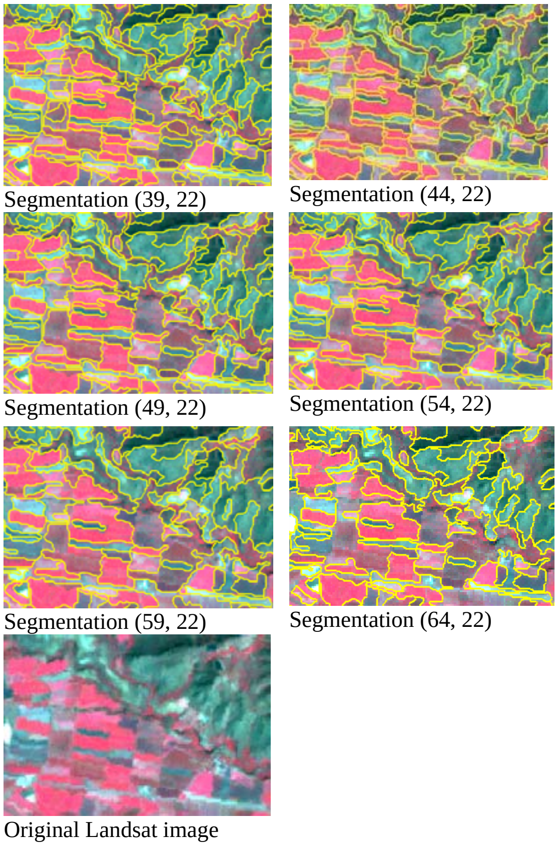


Figure 2. Segmentations with "similarity" threshold from 19 to 64 with intervals of 5, and a constant "area" threshold of 22; and the original landsat image.

4.2. Evaluations of segmentations with objective function

For the ten segmentations, with the similarity threshold increasing from 19 to 64, the intrasegment variance increased from 325.684 to 651.054, and the intersegment spatial autocorrelation between neighbouring segments by Moran's I index decreased from 0.642 to 0.376. With a constant "area" threshold of 22, the larger the "similarity" threshold value the larger the generated segments, the higher the variance indexes, and the lower of the intersegment autocorrelations are. The objective function was calculated and the results present a normal distribution (figure 3), with segmentations based on "similarity" threshold of 39, 44, and 49 leading to the highest objective function values, and objective function value for (44, 22) being the maximum. To obtain the best segmentation result, the choice of parameters depends on the data type, the land cover type, and which and how many spectral bands are used in image segmentation. Espindola *et al.* (2006) tested 2500 combinations of similarity (1-50) and area (1-50) on a single band of Landsat image in a small area to find the optimal combination of both parameters. In practice, multispectral data of large areas are typically used; thus for the selection of segmentation parameters visual inspection and objective function should be combined. Visual inspection can be used to rule out some results that are evidently over-or under-segmented. The objective function can then be used to determine the parameters for the best segmentation results.

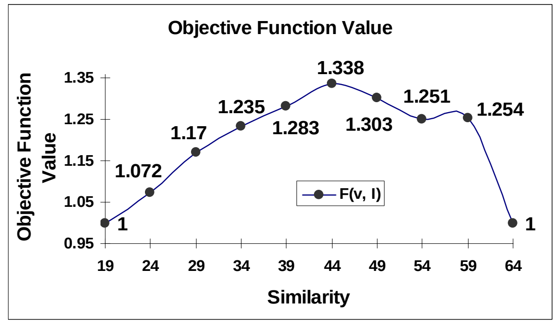


Figure 3. Objective function values.

4.3. Pixel- and segment-based classifications and accuracy assessment

To test the hypothesis that best segmentation results, according to the objective function, also yield the best classification results, the segmented images were classified and their classification accuracies evaluated and compared.

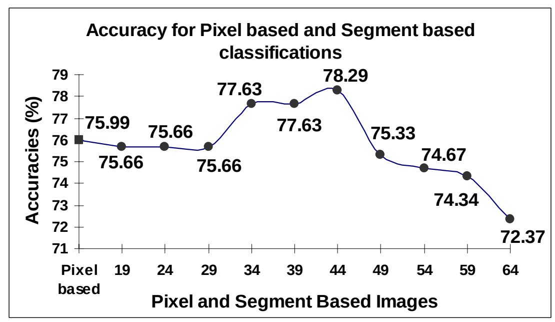


Figure 4. Accuracies of pixel based and segment based classifications.

The accuracy assessment results show that the group of segmentations with the highest objective function value also led to the highest classification accuracy, with accuracy from segmentation (44, 22) being the highest (Figure 4), suggesting that the best segmentations indeed result in highest classification accuracies. However, unlike the objective function values, the accuracy values did not present were not normally distributed. The segmentations on the left side were mostly over-, and on the right under-segmented. In the classification stage, the segments in the over-segmented images could be allocated to their proper class. However, more serious over-segmentation approximates pixel-based image classification. On the other hand, we know of no classification programs that can separate land cover types which are grouped in one segment, i.e. deal with undersegmentation. Segmentation using (44, 22) obtained the highest object function value resulting in classification accuracy 5.92% higher than that obtained by the segmentation with the lowest objective function value. McNemar's test indicates that the difference between these two classification accuracies is significant with p= 0.05, p is the significance level, which shows that the classification from the best segmentation is significantly better than that from the segmentation with a low objective function value, showing that the objective function is indeed an effective way to determine the segmentations to carry out the classifications. Despite the significant effect of different segmentation parameters on the subsequent classification accuracies, the maximum improvement of segmentation-based classifications {(based on (39, 22), segment (44, 22)} only outperformed pixel-based classification by a maximum of 2.3%, not significant with McNemar's test (with p=0.05). Unless segment characteristics, such as shape and size, or contextual and relational information are also used in the classification, even an optimised segmentation does not necessarily lead to improvement over traditional pixel-based classification.

5. CONCLUSIONS

Segment-based classification is commonly seen as leading to improved classification results over pixel-based approaches (Dorren et al. 2003, Geneletti and Gorte 2003, Gitas et al. 2004). This has also fuelled research into optimisation of what is traditionally seen as a trial-and-error approach to segmentation. This paper showed the significant effect of different segmentation parameters on the subsequent classification accuracies. It also showed that there is in fact an optimal segmentation result and the objective function is indeed an effective way to determine the optimal segmentations to carry out the classifications. This research indicates that the classification accuracy increases for optimally segmented images, although such increases are small. The principal limitation may due to that the shape, texture, or contextual information of segments was not used in the classification. Further, optimisation approaches such as the objective function used here or based on other statistical measures (e.g., van Droogenbroeck and Barnich 2005) cannot overcome the image-type and scene dependency of image segmentation.

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References

Benz, U. C., Hofmann P., Willhauck G., Lingenfelder I., Heynen M., 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry & Remote Sensing* 58, pp. 239-258.

Câmara, G., Souza R. C. M., Freitas U. M., Garrido J., 1996. SPRING: Integrating remote sensing and GIS by object-oriented data modelling. *Computers & Graphics,* 20(3), pp. 395-403.

Dorren, L. K. A., Maier, B., and Seijmonsbergen, A. C., 2003. Improved Landsat-based forest mapping in steep mountainous terrain using object-based classification. *Forest Ecology and Management*, 183, pp. 31-46.

Espindola, G. M., Camara, G., Reis, I. A., Bins, L. S., and Monteiro, A. M., 2006. Parameter selection for region-growing image segmentation algorithms using spatial autocorrelation. *International Journal of Remote Sensing*, 27, pp. 3035-3040.

Evans, C., Jones, R., Svalbe, I., and Berman, M., 2002. Segmenting multispectral Landsat TM images into field units. *IEEE Transactions on Geoscience and Remote Sensing* 40, 1054-1064.

Flanders, D., Hall-Beyer, M., and Perenerzoff, J., 2003. Preliminary evaluation of eCognition object-based software for cut block delineation and feature extraction. *Canadian Journal of Remote Sensing*, 29, pp. 441-452.

Foody, G.M., 2004. Thematic Map Comparison: Evaluating the Statistical Significance of differences in Classification Accuracy. *Photogrammetric Engineering & Remote Sensing* 70, pp. 627-633.

Gao, Y., Mas, J. F., Maathuis, B. H. P., Zhang, X. M., and Van Dijk, P. M., 2006. Comparison of pixel-based and object-oriented image classification approaches-a case study in a coal fire area, Wuda, Inner Mongolia, China. *International Journal of Remote Sensing*, 27, pp. 4039-4051.

Giada, S., De Groeve, T., Ehrlich, D., 2003. Information extraction from very high resolution satellite imagery over Lukole refugee camp, Tanzania. *International Journal of Remote Sensing*, 24, pp. 4251-4266.

Gitas, I.Z., Mitri, G.H., Ventura, G., 2004. Object-based image classification for burned area mapping of Creus Cape, Spain, using NOAA-AVHRR imagery. *Remote Sensing of Environment*, 92, pp. 409-413.

Pal, N. R. and Pal, S. K., 1993. A review on image segmentation techniques. *Pattern Recognition,* 26, pp. 1277-1294.

Shackelford A. K., and Davis C. H., 2003. A combined fuzzy pixel-based and object-based approach for classification of high-resolution multispectral data over urban areas. *IEEE Transactions on Geoscience and Remote Sensing,* 41, pp. 2354-2364.

Van Droogenbroeck, M., and Barnich, O., 2005. Design of Statistical Measures for the Assessment of Image Segmentation Schemes. Volume International Conference on Computer Analysis of Images and Patterns (CAIP 2005) of Lecture Notes on Computer Science (LNCS 3691). Springer Verlag, Paris, pp. 280-287