Image Segmentation for the Purpose Of Object-Based Classification

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Abstract— **The main aim of this research is to find optimum segmentation parameters for extracting different land cover classes. A relatively new segmentation approach, multiresolution segmentation, is being examined using two data sets (Landsat and IRS).**

Keywords- multiresolution segmentation; object-based classification; land-cover classification

I. INTRODUCTION

The remote sensing society is currently being offered a wide variety of digital imagery that covers most of the Earth's surface. This up-to-date image data is a promising tool for producing accurate land cover maps. To maximize the benefit of such data, automatic and efficient classification methods are needed. To achieve this objective (for the past years), pixel-based classification has been extensively used.

Currently the prospects of a new classification concept, object-based classification, are being investigated. Recent studies (e.g. [1]) have proven the superiority of the new concept over traditional classifiers. The new concept's basic principle is to make use of important information (shape, texture and contextual information) that is present only in meaningful image objects and their mutual relationships.

In order to obtain those image objects, object-based classification starts by segmenting the entire image. In eCognition (from Definiens Imaging GmbH) the resulting image objects "know" their neighbors and are later classified. The classification process is controlled by a knowledge base that describes the characteristics of output object classes (in the form of fuzzy membership functions).

The main aim of this research is to find the optimum parameters for extracting different land cover classes using a relatively new segmentation approach (multiresolution segmentation). Other objectives include: testing the feasibility of using a single segmentation for successfully extracting all examined land-cover classes and testing the applicability of the new segmentation approach for different data types.

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II. IMAGE SEGMENTATION

A. What is Image Segmentation?

In remote sensing, the process of image segmentation is defined as: "the search for homogenous regions in an image and later the classification of these regions" [2]. Available approaches can be grouped into three categories [3]: point-based (e.g. grey-level thresholding), edge-based (e.g. edge detection techniques) and region-based (e.g. split and merge). In the region-based category, image objects are generated according to a certain homogeneity criteria [4]

B. Multiresolution Segmentation

eCognition offers a relatively new segmentation technique called *Multiresolution Segmentation (MS).* Because MS is a bottom-up region-merging technique, it is regarded as a region-based algorithm. MS starts by considering each pixel as a separate object. Subsequently, pairs of image objects are merged to form bigger segments.

The merging decision is based on local homogeneity criterion, describing the similarity between adjacent image objects. The pair of image objects with the smallest increase in the defined criterion is merged. The process terminates when the smallest increase of homogeneity exceeds a user-defined threshold (the so called Scale Parameter –SP). Therefore a higher SP will allow more merging and consequently bigger objects, and vice versa.

The homogeneity criterion is a combination of *color* (spectral values) and *shape* properties (*shape* splits up in *smoothness* and *compactness*). Applying different SPs and *color/shape* combinations, the user is able to create a hierarchical network of image objects [5].

C. Segmentation Evaluation

Segmentation evaluation techniques can be generally divided into two categories (supervised and unsupervised). The first category is not applicable to remote sensing because an optimum segmentation (ground truth segmentation) is difficult to obtain. Moreover, available segmentation evaluation techniques have not been thoroughly tested for remotely sensed data.

Therefore, for comparison purposes, it is possible to proceed with the classification process and then indirectly assess the segmentation process through the produced classification accuracies.

III. Study Area and Used Imagery

This research focal point is Algiers. With a population of nearly 2.6 million inhabitants and an area of more than 200 square kilometers, Algiers is the capital and major city of Algeria. The study area includes the built-up area of Algiers and surrounding areas of sea, cropland, grassland, and forest.

Two types of image data are used. The first, an IRS-LISS image with a spatial resolution of 20m, has three spectral bands (green, red, NIR -after omitting the short wave IR band) and was acquired in January 2000. The second, a Landsat TM image with a spatial resolution of 30m, has six spectral bands (after omitting the thermal band) and was acquired in September 1997. Omitted bands were not used because of having a lower spatial resolution.

Two vector datasets are used as ground truth: Foundation Feature Data (FFD) and VMap Level 1 data. More information is found in [6].

IV. Implementation

A. Segmentation Criterion

Each image was segmented (in two different eCognition projects) using the previously described MS technique to generate nine different segmentations. Table 1 reports the used SPs and criterion combinations. In the first project, 70% of the criterion dependent on color and 30% on shape. The later factor was divided between compactness and smoothness in the ratio of 8 to 2.

In the second project, more emphasis was given to color (increased from 70% to 80%) and also the importance of smoothness was increased (from 20% to 40%) on the expanses of compactness (decreased from 80% to 60%).

B. Classification

The next step was to classify each of the above segmentation levels into three land-cover classes (built-up, water and vegetation). For this, sets of fuzzy rules were defined.

Rules included both spectral and textural information. For example the built-up class was extracted using two membership functions. The first was the GLCM homogeneity function (must have a value between 0.18 and 0.195). The second was the spectral ratio of the red band (must have a value between 0.24 and 0.255).

Table I. Used Segmentation Criterion

Segmentation Level		SP	Color	Shape		Segmentation Mode
				Smoothness	Compactness	
Project 1	Level 1	8	0.7	0.8	0.2	Normal
	Level 2	13	0.7	0.8	0.2	Normal
	Level 3	18	0.7	0.8	0.2	Normal
	Level 4	18				Spectral difference
Project 2	Level 1	8	0.8	0.6	0.4	Normal
	Level 2	12	0.8	0.6	0.4	Normal
	Level 3	16	0.8	0.6	0.4	Normal
	Level 4	20	0.8	0.6	0.4	Normal
	Level 5	20				Spectral difference

V. Accuracy Assessment

A. Classification Accuracy

Two statistical accuracy assessment techniques were used in this research. The first is the Error Matrix (EM) and it reports three accuracy measures, only the Overall Accuracy (OA) is considered here.

The second is the Kappa statistic table (K^) and in addition to a single K^ value for each land-cover class, it reports and Overall Kappa accuracy (OAK). [2] and [7] contain a detailed description of the above two techniques.

Classification assessment was carried out in Erdas Imagine using the available accuracy assessment tool. 512 random points were generated (using stratified random) and the corresponding ground truth was verified using available ground truth data.

Fig. 1 to 4 reports the classification accuracies for the previously produced segmentations. In those graphs, the five graph lines represent the five accuracy values (OA, OAK, built-up, water and vegetation) for each segmentation level (plotted on the x-axis). While the right y-axis corresponds to the classification accuracy, the left y-axis corresponds to the used SP (represented in the form of columns).

B. IRS Image

Fig. 1 and 2, show that the OA for the IRS image ranges between 81% and 86.7%. However the OK^ is much less (between 0.59 and 0.7). Also it is clear that the water class is easily extracted with K^ of 1 for all segmentations which implies that the segmentation does not have any impact on the extraction of water. This can be due to obvious spectral difference between water and other land-cover classes.

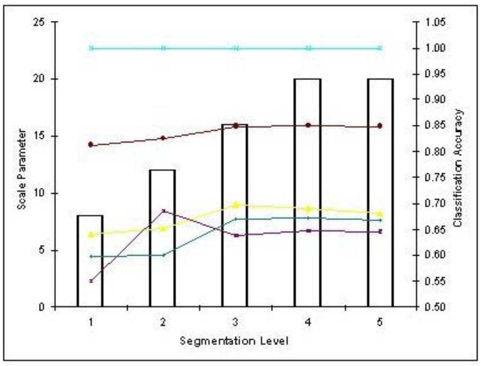
For the built-up class, it is clear that a higher SP produces better results (a maximum K^ off 0.7188 with a SP of 18 and a minimum K^ of 0.6420 with a SP of 8). Comparing projects 1 and 2, it is obvious that the built-up class is better extracted when the importance of the spectral values and compactness of the image object are increased (project 2).

For the vegetation class, although the segmentation criterion parameters have an effect similar to the effect on the built-up class, for vegetation it has a bigger effect as the range of classification values is much bigger (from 0.55 to 0.6852).

D. Landsat Image

Comparing the results obtained from the Landsat image with the IRS results, Fig. 3 and 4 show that the Landsat image produces not only less overall classification accuracies but also less individual classes accuracies.

Also the water class produced less accuracy (mainly due to the difficulties in extracting inland water objects due to the spatial resolution constrain). Finally, it is clear that lines in Fig. 3 and 4 are more horizontal which represent less sensitivity to changes in segmentation.



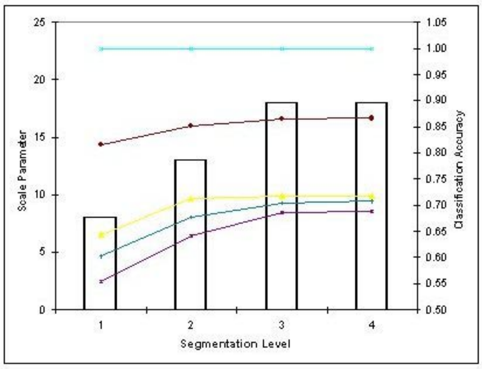
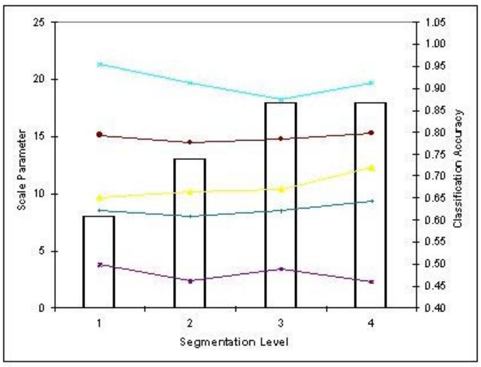


Figure 1. IRS Project 1

Figure 2. IRS Project 2



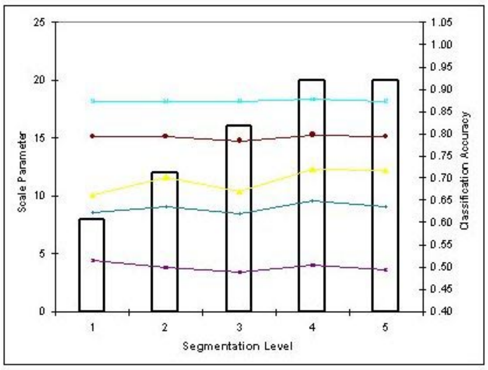


Figure 3. Landsat Project 1

Figure 4. Landsat Project 2

VI. SUMMARY AND CONCLUSION

In this research the effect of segmentation parameters on object-based classification have been studied. This was carried out by applying several segmentation parameters to two kind of imagery (IRS and Landsat). Before using the EM and K^ techniques to assess the classification accuracy, previously created segmentations were classified using texture and contextual information. Using the above accuracy assessment values, four graphs (two for each image data type) representing the relation between used SP and accuracy results were plotted.

Analyzing the above diagrams, the following were the main conclusions points:

1. The IRS image produces better classification results than the Landsat image with multiresolution segmentation.
2. For the IRS image it was possible to find a set of segmentation parameters that produce the best results with all examined land-cover classes. This was not the case with the Landsat image.
3. This set of parameters was composed of a relatively high SP (between 13 and 18) with high emphasis on spectral values (around 80%) and high emphasis on compactness (60%).
4. The IRS image was more sensitive to any change in the segmentation parameters than the Landsat Image. This is due to the higher spatial resolution and therefore the more embedded spatial information.

Future work should focus on two issues. The first, is investigating the prospects of using the suggested (optimum) set of parameters to extract more land-cover and land-use classes. The second is testing the transferability of the suggested segmentation parameters to different geographic locations, with different physical properties.

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