ANALYSIS OF SEGMENTATION PARAMETERS IN ECOGNITION SOFTWARE USING HIGH RESOLUTION QUICKBIRD MS IMAGERY

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ABSTRACT:

For object- oriented classification approaches, main step is the segmentation part of the imagery. In eCognition v.4.0.6 software, with the segmentation process, meaningful objects can be created for following steps. In the experimental imagery with 2.4m ground sampling distance (GSD) has been used and several different parameters e.g. scale, color/shape and smoothness/compactness parameters have been tested accordingly. Additionally, segmentation parameters were set to low and high values and thus, dissimilarity of segmentation results were examined.

1. INTRODUCTION

Segmentation is the subdivision of an image into separated regions. For many years, procedures for image segmentation have been a main research focus in the area of image analysis. Many different approaches have been followed. However, few of them lead to qualitatively convincing results which are robust and applicable under operational settings. One reason is that segmentation of an image into a given number of regions is a problem with a high number of possible solutions. The high number of degrees of freedom must be reduced to the one or the few solutions which satisfy the given requirements. Another reason is that in many cases regions of interest are heterogeneous; ambiguities arise and the necessary discerning information is not directly available. Requirements concerning quality, performance – size of data set and processing time – and reproducibility can be fulfilled at the same time only by very few approaches.

In image segmentation the expectation is in many cases to be able to automatically extract the desired objects of interest in an image for a certain task. However, this expectation ignores the considerable semantic multitude that in most cases needs to be handled to successfully achieve this result, or it leads to the development of highly specified algorithms applicable to only a reduced class of problems and image data.

Of course there is a variety of methods for generating image objects which cannot be summarized here, and each of them has its advantages and disadvantages. Some are fully automated while others are semi-automatic. Giving a rough overview, according to recent research in image understanding, image segmentation methods are split into two main domains: knowledge driven methods (top-down) vs. data driven methods (bottom-up). In top-down approaches the user already knows what he wants to extract from the image, but he does not know how to perform the extraction. By formulating a model of the desired objects, the system tries to find the best method(s) of image processing to extract them. The formulated object model gives the objects' meaning implicitly. In bottom-up approaches the segments are generated based upon a set of statistical methods and parameters for processing the whole image. As such, bottom-up methods can also be seen as a kind of data abstraction or data compression. But, as with clustering methods, in the beginning the generated image segments have no meaning, they can better be called: image object primitives. It is up to the user to determine what kind of real world objects the generated image objects represent. The basic difference between both approaches is: top-down methods usually lead to local results because they just mark pixels or regions that meet the model description, whereas bottom-up methods perform a segmentation of the complete image. They group pixels to spatial clusters which meet certain criteria of homogeneity and heterogeneity (eCognition User Guide 4, 2004).

In object-oriented classification approaches, segmentation is not an aim in itself. As regards the object-oriented approach to image analysis, the image objects resulting from a segmentation procedure are intended to be rather image object primitives, serving as information carriers and building blocks for further classification or other segmentation processes. In this sense, the best segmentation result is the one that provides optimal information for further processing (Hofmann, et al., 1998).

eCognition v 4.0.6 object-oriented image analysis software offers a relatively segmentation technique called multiresolution segmentation. In this study, the positive and negative effects of segmentation parameters were tried to find out. So in eCognition v4.0.6 software, segmentation parameters were changed one by one and the segmentation results were monitored by using Quickbird MS image with 2.4m GSD.

2. IMAGE SEGMENTATION IN ECOGNITION SOFTWARE

As mentioned above, eCognition software segmentation technique used called as multiresolution segmentation. Multiresolution segmentation is a bottom up region-merging technique starting with one-pixel objects. In numerous subsequent steps, smaller image objects are merged into larger ones. Throughout this pairwise clustering process, the underlying optimization procedure minimizes the weighted heterogeneity nh of resulting image objects, where n is the size of a segment and h an arbitrary definition of heterogeneity. In each step, that pair of adjacent image objects is merged which stands for the smallest growth of the defined heterogeneity. If the smallest growth exceeds the threshold defined by the scale parameter, the process stops. Doing so, multiresolution segmentation is a local optimization procedure.

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To achieve adjacent image objects of similar size and thus of comparable quality, the procedure simulates the even and simultaneous growth of segments over a scene in each step and also for the final result. Thus, the procedure starts at any point in the image with one-pixel objects. A treatment sequence based on a binary counter guarantees a regular spatial distribution of treated objects. However, for obvious reasons, such a sequence contains a stochastic, historical element (eCognition User Guide 4, 2004).

In general expression, spectral or color heterogeneity is described as;

$$h = \sum_{c} w_c \sigma_c \tag{1}$$

Here, sum of the standard deviations of spectral values in each layer weighted with the weights for each layer gives the heterogeneity.

It is useful in most cases to mix the criterion for spectral heterogeneity with a criterion for spatial heterogeneity, in order to reduce the deviation from a compact or smooth shape. Heterogeneity as deviation from a compact shape is described by the ratio of the de facto border length *l* and the square root of the number of pixels forming this image object.

$$h = \frac{l}{\sqrt{n}} \tag{2}$$

A further possibility of describing shape heterogeneity is the ratio of the de facto border length *l* and the shortest possible border length b given by the bounding box of an image object parallel to the raster.

$$h = \frac{l}{b} \tag{3}$$

With the assistance of expressions given above, extra expressions have been produced in eCognition software. Furthermore another important subject is eCognition runs these expressions in a hierarchical frame. So both the adjacent objects and the sub or super objects effects each other. Hierarchical structure can be seen in Fig. 1.

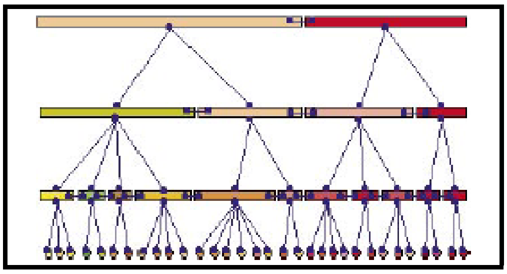


Fig.1: Hierarchical structure of image objects.

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 userdefined 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 (Darwish et al., 2003).

All expressions given above and used under eCognition software are hidden and user can reach only parameters allowed by software – as mentioned above scale parameter, shape-color and compactness-smoothness parameters if shape parameter is activated – and all these parameters are only values which can be entered into expressions as variables and sum of dashed parameters is 1.0.

3. TESTFIELD AND USED DATA

The testfield Zonguldak is located in Western Black Sea region of Turkey. It is famous with being one of the main coal mining areas in the world. Area has a rolling topography, in some parts, with steep and rugged terrain. While partly built city area is located alongside the sea coast, there are some agricultural lands and forests in the inner part of the region (Marangoz et al., 2004).

In this study, the analysis of segmentation parameters in eCognition object-oriented image analysis software were handled using QuickBird MS image of Zonguldak testfield (see Fig. 2). At all the processing phase, subset of the image was used because of long processing time of whole image.

Fig.2: QuickBird MS image of Zonguldak testfield.

QuickBird MS image of this testfield was purchased from Nik Inc. which is the regional affiliate of DigitalGlobe and located in Istanbul, Turkey. Important characteristics included in the metadata files of this image are given in Table 1.

Date, Time	23/05/2004, 08:39:55 GMT
Nominal collection azimuth (deg.)	61.0
Nominal collection elevation (deg.)	85.9
Sun angle azimuth (deg.)	139.1
Sun angle elevation (deg.)	64.7
Nadir angle (deg.)	3.9
Image size (pixels in row, column)	24.572 x 25.500
Reference height (m)	265.66

Table 1: Characteristics of QuickBird image of Zonguldak testfield.

4. CASE STUDY

The Zonguldak testfield of QuickBird MS image was segmented using the previously described multiresolution segmentation technique to generate 5 different object-oriented segmentations by generating two projects. One segmentation level in Project 1 and four segmentation levels in Project 2 were produced.

At this segmentation phase, three visible spectral bands of image were used. Near IR band included in QuickBird MS imagery was not used because this band reflects both real green objects and roofs of buildings at the same time. This kind of reflection causes wrong segmentation results which effects subsequent classification phase.

Table 2 reports the used scale parameters and criterion combinations by two projects. As can be realized that the smaller scale decreases the dimensionality and dividing the object into the sub-groups, while the larger scale combines the multi-segments into one (see Fig. 3).

Segmentation Level		Bands	Scale Parameter	Shape Parameter		Color Parameter	Segmentation Mode
				Compactness	Smoothness		
Project 1	Level 1	1,2,3	25	0.3	0.7	0.9	Normal
Project 2	Level 1	1,2,3	5	1.0	0	0.6	Normal
	Level 2	1,2,3	10	0.7	0.3	0.8	Normal
	Level 3	1,2,3	20	0.5	0.5	0.9	Normal
	Level 4	1,2,3	25	0.3	0.7	0.9	Normal

Table 2: Segmentation parameters in Project 1 and Project 2.

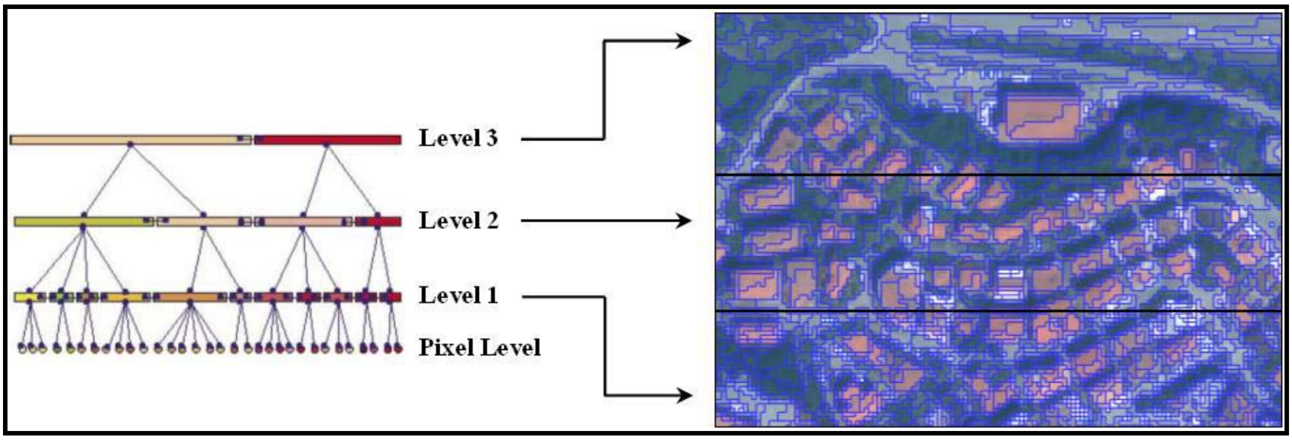
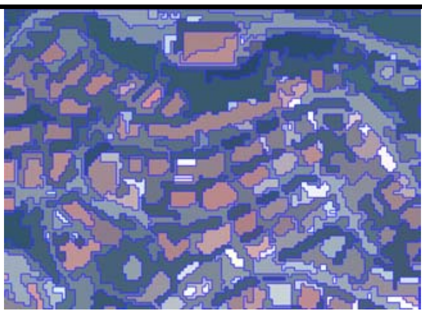
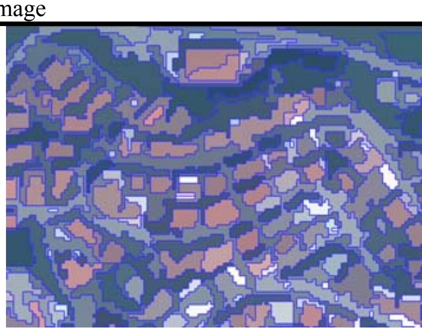


Fig. 3: Hierarchical net of image objects derived from image segmentation level 1 (5 pixels scale parameter), level 2 (10 pixels scale parameter) and level 3 (20 pixels scale parameter) in Project 2.

Subset of QuickBird MS image



Level 1 in Project 1



Level 4 in Project 2

Fig. 4: Segmentation levels using subset of QuickBird MS image

As seen in Fig. 4, the segments were generated in different shape, although segmentation parameters of segmentation levels were same in both projects. This situation can be explained as; all super-objects have their own mean gray value, so on each level segmentation expressions give different results.

Furthermore, numbers of generated segments which have same segmentation parameters in both projects have been resulted differently (see Table 3). As it is seen in the table, Level 1 of Project 1 produced more segments than Level 4 of Project 2. However level 1 of Project 1 has some mixed segments although level 4 of Project 2 does not have mixed objects at the same point. This result can be seen in Figure 4 – a mixed object lies under the largest building in images.

Segmentation Level		**Number of Generated Segments**
Project 1	*Level 1*	*17029*
Project 2	Level 1	294788
	Level 2	86751
	Level 3	25275
	Level 4	*16985*

Table 3: Number of segments generated after segmentations at project 1 and project 2.

5. CONLUSION

Nowadays there are many applications using object-oriented image analysis. eCognition is one of the software which can be used for this approach. In this software, segmentation is the main process and its aim is to create meaningful objects from images. Segmentation is the sub-phase of classification. Here, some parameters e.g. scale, shape-color and smoothness-compactness are used and they should be assigned as accurate as possible, of course, suiting with the reality. Many times it is said that derived segmentation results were suitable for image which resulted in user's object-oriented application. But generally, it is more complex than this, for example, a suitable segmentation level of QuickBird MS image which derived in this study may not be suitable for another image even if it is taken by same satellite. This situation may be caused by sun elevation, acquisition time, topography of testfield etc. Even if same condition is possible, segmentation levels must be repeated as same as done before, step by step.

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