FROM PIXELS TO GRIXELS: A UNIFIED FUNCTIONAL MODEL FOR GEOGRAPHIC OBJECT-BASED IMAGE ANALYS

I. Lizarazo [a,*] , P. Elsner [b]

[a]Cadastral and Geodetic Engineering Department, Universidad Distrital, Carrera 7 No. 40-53, Bogota, Colombia
ilizarazo@udistrital.edu.co
[b]School of Geography, Birkbeck College, University of London, Malet Street, London, WC1E 7HX UK
p.elsner@bbk.ac.uk

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ABSTRACT:

Geographic Object-Based Image Analysis (GEOBIA) aims to better exploit earth remotely sensed imagery by focusing on building image-objects resembling the real-world objects instead of using raw pixels as basis for classification. Due to the recentness of the field, concurrent and sometimes competing methods, terminology, and theoretical approaches are evolving. This risk of babelization has been identified as one of the central threats for GEOBIA, as it could hinder scientific discourse and the development of a generally accepted theoretical framework. This paper contributes to the definition of such ontology by proposing a general functional model of the remote sensing image analysis. The model compartmentalizes the remote sensing process into six stages: (i) sensing the earth surface in order to derive pixels which represent incomplete data about real-world objects; (ii) pre-processing the pixels in order to remove atmospheric, geometric, and radiometric distortions; (iii) grouping the pre-processed pixels (prixels) to produce image-objects (grouped pixels or grixels) at one or several scales; (iv) feature analysis to examine and measure relevant spectral, geometric and contextual properties and relationships of grixels in order to produce feature vectors (vexcels) and decision rules for subsequent discrimination; (v) assignation of grixels to pre-defined qualitative or quantitative land cover classes, thus producing pre-objects (preliminary objects); and (vi) post-processing to refine the previous results and output the geographic objects of interest. The grouping stage may be analized from two different perpectives: (i) discrete segmentation which produces well-defined image-objects, and (ii) continuous segmentation which produces image-fields with indeterminate boundaries. The proposed generic model is applied to analyze two specific GEOBIA software implementations. A functional decomposition of discrete segmentation is also discussed and tested. It is concluded that the proposed framework enhances the evaluation and comparison of different GEOBIA approaches and by this is helping to establish a generally accepted ontology.

1 INTRODUCTION

GEOBIA is a GIScience discipline devoted to developing automated methods to partition remote sensing (RS) images into meaningful image-objects, and assessing their contextual and spectral characteristics at different spatial and temporal scales (Hay and Castilla, 2008). In recent years, successful application of GEOBIA concepts, methods and tools has been reported in different application domains (Blaschke et al., 2006) (Yan and Bauer, 2006). As an emerging discipline, GEOBIA lacks a unified and shared theory of image-objects and geographic objects. Instead, a competing number of definitions and methods are evolving and much more attention seems to be paid to the application of current software implementation and prototypes than to general concepts and models able to promote geographic knowledge and intelligence. In the absence of such a theory, a risk of babelization is threatening GEOBIA future (Hay and Castilla, 2008). Hence, there is a need for building a formal ontology of GEOBIA objects and processes which provides the basis for exchange of information and serves as a framework for cross-disciplinary collaboration between different domains of GIScience. This paper attempts to establish a generic conceptual framework of the geographic object-based image analysis process. It focuses on the transformation of the image's constituent elements through the different stages of the process, from the raw pixels to the final structures representing geographic objects. This paper is organized as follows. Section 2, reviews ontological concepts for geographic information. Section 3 discusses an ontology for remotely sensed images. Section 4 proposes a framework for geographic object-based image analysis. Section 5 discusses image segmentation and section 6 concludes.

2 GEOGRAPHIC ONTOLOGIES

2.1 GEOBIA Ontology: a brief review

One of the main motivations for building GEOBIA is the increasing need for an efficient extraction of information from remotely sensed images and its integration into GIS databases. GEOBIA approach may be seen as an improved image analysis method in the continuum of classification methods. What makes GEOBIA special may be explained by two characteristics: (i) image segmentation, at one or several scales, as part of the object relationship databases building; and (ii) image classification querying both spectral and spatial image-objects parameters (Blaschke et al., 2006).

Since GEOBIA relies on remotely sensed data, and generates GIS ready output, it can be seen as the critical bridge between the raster domain of remote sensing and the predominantly vector domain of GIS. The 'bridge' linking both sides of these domains is the generation of classified image-objects representing geographic objects (Hay and Castilla, 2008). In simple terms, image-objects are "groups of pixels with meaning in the real world" (Schneider and Steinwender, 1999). The relationship between real-world objects and image-objects must be made explicit by means of spatial analysis and semantic rules (Blaschke et al., 2006).

Because of the close link between remote sensing and GIS it is sensible to integrate GEOBIA ontology into a general theory of geographic representation. A substantial contribution to such a theory relies on the concepts of geo-objects and geo-fields which will be discussed in the next section.

2.2 An ontology for geographic information

Goodchild et al. (2007) have proposed a general ontology for geographic representation in which all information may be reduced to a very basic form, the geo-atom. A geo-atom is defined as an association between a point location in space-time and a property. A geo-atom can be written as a tuple $\langle x, Z, z(x) \rangle$ where x defines a point in space-time, Z identifies a property and $z(x)$ defines the particular value of the property at that point. In this framework, both discrete geographic objects (geo-objects) and continuous fields (geo-fields) are simply aggregations of geo-atoms (Goodchild et al., 2007).

A geo-object is defined as an aggregation of points in space-time whose geo-atoms meet certain requirements, such as having specified values for certain properties. The dimensionality of geo-objects is constrained by the space in which they are embedded. For example, a geo-object which is embedded in a space of two horizontal dimensions and time, may be a point, line or area. The spatial extent of a geo-object can be established by *fiat* boundaries, as for example when census zones are defined by administrative decision. It can also have *bona fide* boundaries if the spatial extent reflects some form of internal cohesion or homogeneity, for example when geo-objects represent individual trees, houses, or geographic regions (Goodchild et al., 2007).

A geo-field defines the variation of one or more properties over a domain of space-time D. As such, it constitutes an aggregation of geo-atoms over space by property Z, irrespective of value $z(x)$. A geo-field for a single property such as elevation is termed a scalar geo-field, while a vector geo-field might describe the spatial (and temporal) variation of a phenomenon such as wind or temperature over a domain. In principle, any geo-field over a finite domain D aggregates an infinite number of geo-atoms. Thus, unless a geo-field can be represented accurately by a mathematical function, in practice it is necessary to sample, discretize or interpolate it to store it in a container of finite size (Goodchild et al., 2007).

In current GIS practice, a common way of representing geo-fields is using some kind of discretization. One of them, the piecewise constant representation in a regular grid of cells (normally rectangular), is of particular importance for remote sensing image analysis. The key point to note here is that the discrete picture elements (pixels) utilized to represent a geo-field normally have no meaning in reality but exist solely for the purpose of measurement or representation.

3 AN ONTOLOGY FOR REMOTE SENSING IMAGES

3.1 Do images represent geo-fields or geo-objects?

Following Goodchild et al. (2007) geographic ontological concepts, remotely sensed images can be considered as a subclass of geo-fields. Therefore, an image is a 2-dimensional function, arising from the sampled spectral signal of a region of the earth as measured by a passive or active sensor. Nevertheless, viewing images as geo-fields of electro-magnetic energy values is just the starting point for their ontological characterization (Camara et al., 2001).

Remotely sensed images may also be seen as containers of an implicit set of objects which have to be identified by manual or semi-automated image analysis procedures. In this view, the interpretation may focus on extracting *fiat* objects (e.g. land use units whose boundaries result from cognitive actions) or *bona fide* objects (e.g. land cover units whose boundaries exist in nature). In the image interpretation process, *fiat* image-objects are delineated and created. These image-objects owe their existence to (i) the notion of a corresponding geo-object in the world, (ii) an act of measurement (in this case the remote sensing process), and (iii) a creative human act of spatial analysis (Camara et al., 2001). Although this perspective captures a fundamental component of the ontology of images and forms the basis for a large set of image classification techniques, it is still incomplete. In many cases, instead of a corresponding geo-object, the relevant real world object is better represented as a geo-field, as for example when the image analysis focuses on the study of land surface biogeophysical variables like LAI (Leaf Area Index) or the fraction of the absorbed PAR (Photosynthetically Active Radiation) by green vegetation (Camara et al., 2001). In such cases, there are no boundaries to identify or to delineate.

Therefore, both of the two ontological descriptions of remotely sensed images have to be used to support the full process of knowledge representation for image data analysis (Camara et al., 2001). Images are geo-fields at the measurement level but the product of the image analysis process are new images whose nature is dual: they may be either geo-objects (when estimating categorical variables like land cover classes) or geo-fields (when estimating continuous variables like land surface albedo). Even more, in some cases, interpreted images may correspond to a special sub-class of geo-objects termed field-objects, that is, geo-objects with internal heterogeneity conceptualized as a field (Goodchild et al., 2007). For example, a processed MODIS image may comprise geo-objects with boundaries defined by the limits of land cover, and an internal structure defined by the variation of such field-like properties as land surface temperature or emissivity.

3.2 Knowledge representation on images

Camara et al. (2001) propose that remotely sensed images are ontologically instruments for capturing landscape dynamics. This view focuses on the ontological characterization of images on the search for changes instead of the search for content. Its emphasis is not only on object matching and identification procedures, but on capturing dynamics over a finite landscape. Hence, the phenomenon domain for the images has three distinct, but interrelated components:

- A physical ontology, which describes the physical process of image creation. Typical concepts here include spectral response, backscatter and Lambertian target.
- A structural ontology, which includes the geometric, functional, and descriptive structures than can be extracted from or detected in the image by means of feature extraction, segmentation, and classification techniques. Typical concepts for this ontology include geometries as lines and regions, and functional descriptions such as spectral response curve, optical flow and light intensity gradient.
- A methodological ontology, consisting of a set of algorithms and data structures, which represent reusable knowledge in the form of image processing techniques that can be used to transform the image from the physical level to the structural level.

While this phenomenological ontology may be considered as neutral or observer-independent, scientific disciplines conceptualize the world in the particular scope and context of their knowledge domains. A given geographic object, for example an urban area, may be seen as a discrete partition of space into land cover units for planners whereas it may be seen as a a radiative field (depending on surface geometry, land use and land cover) for climatologists. We believe that, if GEOBIA is to become a bridge between remote sensing and GIS applications, a generic ontology for image-regions, able to encompass both image-objects and image-fields, need to be developed.

As a discipline of GIScience, GEOBIA ontological definitions may be based on the theoretical primitives of geographic representation. As a consequence, GEOBIA processes would be able to account for the creation of knowledge from the raw input image to the final interpreted image. In the next section, we propose an ontological framework for image analysis who attempts to advance on such path. This framework is generic to accommodate both quantitative and qualitative analysis of remotely sensed images.

4 A GENERAL FRAMEWORK FOR GEOGRAPHIC OBJECT-BASED IMAGE ANALYSIS

4.1 Image Analysis Process

Our focus lies on the characterisation of the generic image analysis process which changes the structural elements of the image, from the raw pixel data collected by the sensor to the final elements representing geographic objects in the application domain. Figure 1 shows the image analysis process as the sequential development of six distinct and interrelated stages: sensing, pre-processing, grouping, feature analysis, assignation, and post-processing. Each stage is a function which transforms the information contents of the image elements. This representation of the image analysis process suggests a bottom-up information flow, from images with no abstraction to the higher abstraction needed for image understanding. Note that the proposed framework describes the processes which transform image data from the physical reality which is remotely sensed to the human 'construction' (conceptualization) of the geographic objects. It goes from observations through pixels and groups of pixels before providing the target objects of interest. Note also that the proposed flow not need to be unidirectional and that feedback loops and knowledge inputs may occur at any stage of the process. Every stage of the proposed framework is discussed in detail in the following sections.

4.1.1 Sensing: Imaging the earth surface leads to a collection of discrete point measurements of a specific property which is dependent on sensor properties and deployment. Spectral sensors provide a regular array of data (normally arranged as rectangular cells) related to electromagnetic signal of a surface. Image pixels store a value expressing reflected energy. As such, image pixels correspond to some degree to real-world geographic objects. However, the location of the pixel's spatial boundaries is arbitrary and do not match real world surfaces. Neither do pixel's spectral and radiometric boundaries. These three-dimensional boundaries are a function of the sensor capabilities which, in turn, are guided by user-defined objectives. In essence, pixels are fiat objects whose characteristics influences greatly the subsequent stages of the image analysis process.

4.1.2 Pre-processing: Pre-processing of satellite images commonly comprises a series of sequential operations, including atmospheric correction or normalization, image registration, geometric correction, and masking (e.g., in order to ignore clouds, water, or other irrelevant features for a given application). Image

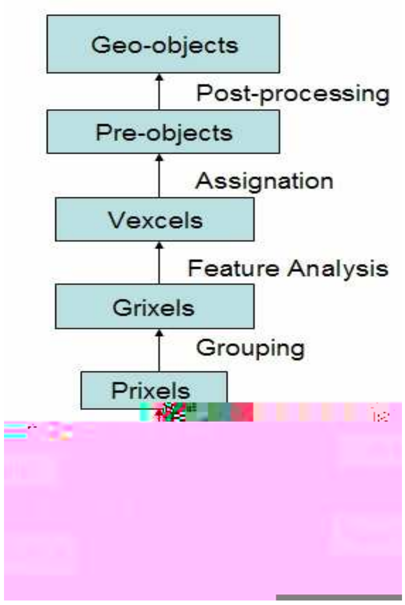

Figure 1: Ontological framework for remote sensing image analysis.

pre-processing outputs pre-processed pixels (prixels). When atmospheric correction techniques are applied, interference caused by water vapour content and aerosol optical depths are removed or attenuated. In such cases, output prixels values represent an accurate estimate of the reflectance of the earth surface. Often, the pre-processing stage aims also to create additional bands or channels of information, as for example, when textural components or vegetation indexes or edges are extracted from the original bands. In such cases, pre-processed images contain both pixels (from the original images) and prixels (from the output new bands).

4.1.3 Grouping: By applying one or several algorithms that are part of the method ontology, this process results in a set of grouped pixels (grixels) or structures strongly related to the measurement device properties and its interaction with the physical landscape. These structures may be geometric (e.g. image-regions extracted by a segmentation procedure) or thematic (e.g. vegetation indexes obtained from multi-temporal images). Grixels are fiat objects which can be described either as well-defined geo-objects or as spatially continuous geo-fields. Therefore, as it will be discussed in section 5, discrete segmentation may be seen as an special case of continuous segmentation. It is important to note that grixels can be obtained at one or several spatial, spectral or temporal scales.

4.1.4 Feature Analysis: At this stage, spectral, contextual or geometric attributes of grixels are analyzed and related to real world objects of interest. A collection of attributes (also known as feature vector) is developed for every grixel in the image. Therefore, the output of this stage is a vector of features for every grixel (or, in other words, a vecxel). Selection of the most relevant attributes is carried to determine the best set of features. In addition, existing knowledge is input to the process in several forms like training samples, semantic networks or decision rules.

4.1.5 Assignation: The output of this stage are preliminary objects (pre-objects) which are expected to be closely related to real-world geo-objects. This stage may be a classification in which cells are given a value expressing their allocation to a qualitative land-cover class. It may be also the estimation of a quantitative variable, in which cells may keep their unique values or be classified into a predefined range of numeric attribute values.

4.1.6 Post-processing: Refining of the previous output using filtering or simulation techniques leads to polished structures which hopefully correspond closely to real-world geo-objects. The output objects can be geo-atoms, geo-objects, geo-fields or field-objects. In the case of geo-objects, this stage usually includes raster to vector conversion. In any case, this stage usually includes analysis of spatial and thematic accuracy and geographic metadata creation.

It should be noted that the described framework is iterative in nature and a number of loops may occur in its execution. Knowledge input is not restricted to the Feature Analysis stage where user interaction is a requirement to make explicit the mapping between image-regions and real world geographic objects. It may occur at any stage of the image analysis process, as for example when entering training samples as input for supervised segmentation or classification. Overall quality evaluation of the image analysis is usually conducted at the end of the process but intermediate quality checks may be conducted after every step to make a decision about its correctness. Moreover, repeated cycles of the image analysis process may lead to scheduling new flight campaigns (or satellite orbits), improving sensor design or advancing image processing algorithms.

4.2 Image analysis process in GEOBIA software implementations

In this section, the proposed framework is applied via a brief analysis of two mainstream image analysis applications: *Definiens* and *ENVI*. *Definiens* (formerly *eCognition*) is a popular implementation of the geographic object-based image analysis process. *Definiens* provides users with advanced capabilities for the following GEOBIA stages (Benz, 2001):

- Pre-processing: capabilities for masking.
- Grouping: capabilities for producing a hierarchical network of segments at different scales.
- Feature Analysis: it offers a rich set of measures on spectral, textural, geometric, contextual and hierarchical properties of image-objects.
- Assignation: two basic choices for classification are available: sample-based classification using nearest neighbour classifier; and rule-based classification, using expert knowledge and fuzzy or crisp logic for rule definition.
- Post-processing: capabilities for filtering classified images and raster-vector conversion.

Definiens allows users to introduce knowledge in the image analysis process by defining relationships between between image-objects and target geographic objects or classes. A process tree can be used to select appropriate analysis steps and automate the image classification process.

The *Definiens* segmentation approach is an iterative process. Users must decide how much color (spectral similarity), how much shape (compactness and smoothness similarity), and also how large the regions (scale parameter) shall be. There are not satisfactory answers yet to every question and users have to decide using both logic and intuition. This issue is alleviated by using multi-scale segmentation, that is, outputting image-objects at several levels of detail and defining hierarchical relationships among them.

The *ENVI Feature Extraction* module is a recent implementation of the GEOBIA process. As a result, *ENVI* software provides a full range of capabilities for image analysis as follows:

- Pre-processing: capabilities for atmospheric correction, radiometric normalization, geometric correction, and masking.
- Grouping: capabilities for producing segments at a given spatial scale. Merging and refining may be conducted as a subsequent step.
- Feature Analysis: it offers a rich set of measures on spatial, spectral and textural properties of image-objects.
- Assignation: two basic choices for classification are available: example-based classification and rule-based classification. The latter includes options for defining fuzzy rules.
- Post-processing: capabilities for editing vectors, spatial enhancement of classified images, thematic accuracy evaluation and raster-vector conversion.

The *ENVI* segmentation approach is an iterative approach which is supported by pre-visualization of the output. Users define a single parameter (scale) and can later refine obtained segments. In addition, ENVI provides a set of tools that allow image analysts to automate image processing routines.

Common capabilities (and differences) between the two GEOBIA software implementations become apparent when analyzed using the proposed workflow. However, our proposed framework may be more detailed. Every stage of the image analysis process can be further examined by splitting it into more detailed actions or tasks. Any action may be described in a generic way to be able to accommodate one or another specific implementation technique. As an illustrative example, in next section we analyze the segmentation process (a special case of the generic Grouping stage) which has been identified as a critical task in the GEOBIA approach (Baatz and Schape, 2000).

5 IMAGE SEGMENTATION

5.1 A general view of segmentation

Segmentation is the partition of an image into meaningful regions that are, in someway, related to real world objects. Image-regions can be produced by segmentation at one single spatial scale or at several nested scales. Image-regions are usually interpreted as discrete image-objects with very well defined boundaries, that is, as a set of non-overlapping, space-exhausting polygons. This approach for image segmentation has proven to be very useful in a great number of applications (Blaschke et al., 2006). Figure 2 shows the discrete approach for image segmentation, i.e. image-objects are disjoint and homogeneous image-regions expressing belonging of a cell either to Region A or Region B. Note that the segmentation output is a single image comprising discrete image-objects.

However, in many cases, the existence of noisy images and spectral ambiguity of target classes may call for building image-regions with indeterminate boundaries. In such cases, image-regions can be modelled using partial belonginess, that is, as collections of grixels with associated membership functions to regions. In other cases, as it was discussed earlier, geographic objects of interest simply do not have well defined boundaries. In any of these cases, image-regions can be better described as image-fields and referred to as continuous image-regions. There will be as many image-fields as n regions exist. For each location x, a membership function $m(x)$ gives the degree of membership of the grixel to every image-region. Figure 3 shows this continuous approach

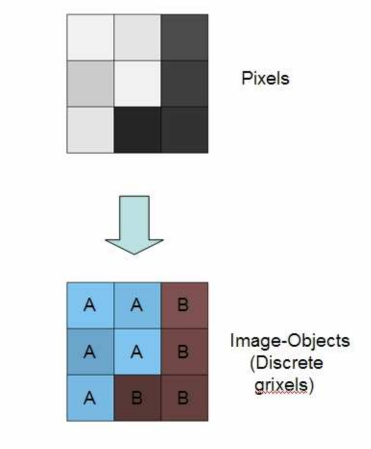

Figure 2: Discrete image segmentation.

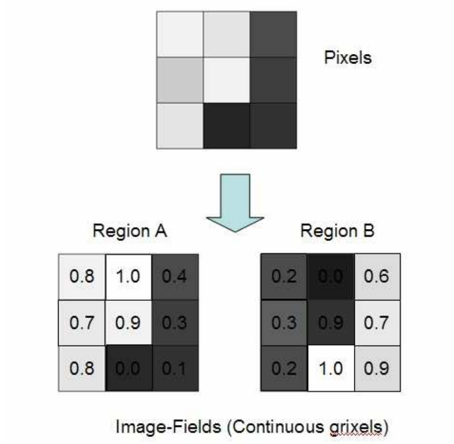

Figure 3: Continuous image segmentation.

for image segmentation, i.e. image-fields are overlapping and heterogeneous image-regions expressing degrees of membership of cells to both Region A and Region B. Note that, the segmentation output is a set of n images comprising continuous image-fields (one image for every target region).

According to the foregoing concepts, we suggest to consider discrete segmentation as a special case of the more general continuous segmentation. However, appropriate methods and structures to store and manipulate continuous image-regions are to be developed in order to advance GEOBIA on that way (Lizarazo and Elsner, 2008). The remaining of this paper analyses the discrete segmentation stage.

5.2 Discrete segmentation functional model

A functional model of discrete segmentation offers a unified view of the process which may be useful for comparison of different techniques and methods. Figure 4 depicts an adapted version of a model originally proposed for computer vision (Zouagui et al., 2004). It is an iterative process composed of five blocks: measurement, criteria building, control, modification and stop.

The Measurement block is in charge of compute at each iteration k a set of M scalar measures expressing some value of homogeneity or dis-similarity for each region n among the N regions of the image. These measures are related to the region homogeneity and the boundary gradients or the neighborhood between adjacent regions (i.e. gray level variance, gray level mean, area, local deviation from mean, clique energy, mean square error, local distance, point displacement). The Measurement block needs as input the original image and the current segmented image.

The Criteria block receives these measures and builds a criteria scalar $C^k(n) = f(F^k(i,n))$ for each region n that express homogeneity for each region (i.e. additive combination, inverse, embedded, magnitude). The Control block verifies if the region has fulfilled the homogeneity parameter (i.e. thresholding, derivative, maximum, minimum) or instead if needs to evolve. It takes as input the criterion values $C^k(n)$ and produces the control value $E^k(n)$ for each region n. If $E^k(n)$ is null, this means this region has reached the required quality.

The Modification block process the current region according to the technique selected (i.e. orthogonal splitting, fixed control point displacement, pixel labeling, histogram thresholding, merging, dilation, contraction, adaptive control point displacement). The Stop block checks if it is necessary or not to continue the iteration.

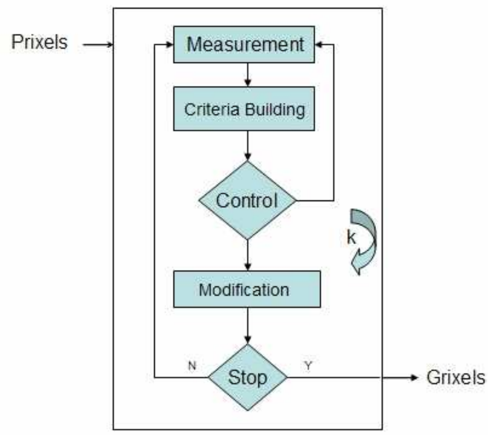

Figure 4: Functional model for discrete segmentation.

Image segmentation in *Definiens* is a multiresolution, bottom up, region-merging technique starting with one-pixel objects. Image objects are extracted from the image in a number of hierarchical segmentation levels and each subsequent level yields image objects of a larger average size by combining objects from the level below, which represents image information on different scales simultaneously.

Objects are grouped into a larger object based on spectral similarity, contrast with neighboring objects and shape characteristics of the resulting object. These three characteristics are grouped in a single parameter called heterogeneity (Yan and Bauer, 2006). Throughout a single segmentation step, the underlying optimization procedure minimizes the heterogeneity of resulting image objects weighted by their size. A segmentation step is finished when very original object is assigned to the optimal higher level object. To achieve adjacent image objects of similar size and thus of comparable quality, the procedures simulates an even and simultaneous growth of objects over a scene in each step and also for the final result.

In Figure 5, *Definiens* segmentation approach is depicted using the functional model described above. Spectral homogeneity (i.e. color) is measured using size and standard deviation of each region in n spectral layers weighted according to user preferences. Compactness is measured as $n_m l_m / b_m$ where n is the size of each region, l is the perimeter of the region and b is the perimeter of a minimum box bounding each region. Smoothness is measured as $n_m lm/(n_m)^{0.5}$. Connected regions are merged only when region size is below a predefined size known as $scale$ parameter.

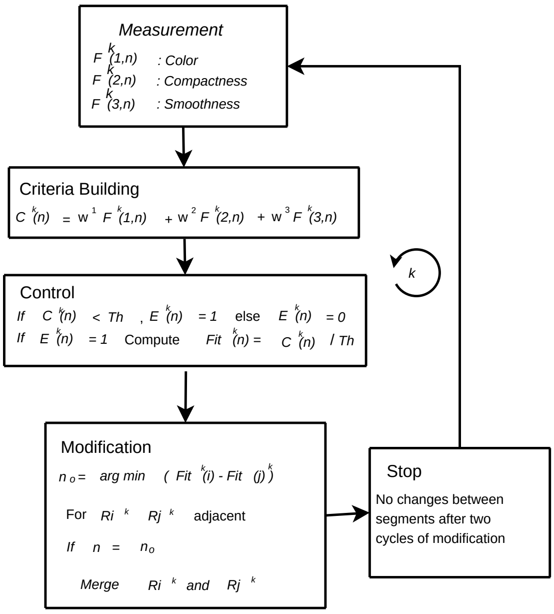

Figure 5: Discrete segmentation as implemented in *Definiens*.

6 CONCLUSIONS

This paper proposes a unified framework for geographic object-based image analysis process. It is based on recent theoretical developments of geographic representation in GIS and aims to contribute to a better integration between remote sensing and GIS applications. It is able to accommodate different approaches to estimate land surface properties, either the qualitative classification of land cover or the quantitative estimation of bio-geo-physical variables. It uses a bottom-up description of the image analysis process where structural properties of the image and abstraction are changed by generic functions or stages. The proposed framework may serve to analyze different GEOBIA software implementations and to compare the particular ways they use to accomplish each stage of the process. More important, critical processes of the GEOBIA image analysis approach like the segmentation stage can be extended and generalized to allow the existence of both discrete image-objects and continuous image-fields.

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