MULTI-RESOLUTION, OBJECT-ORIENTED FUZZY ANALYSIS OF REMOTE SENSING DATA FOR GIS READY INFORMATION

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ABSTRACT

Remote sensing from airborne and space borne platforms provide valuable data for mapping, environmental monitoring, disaster management and civil and military intelligence. However, to explore the full value of these data, the appropriate information has to be extracted and presented in standard format to import it into geo-information systems and thus allow efficient decision processes.

Object-oriented analysis can contribute to powerful automatic and semi-automatic analysis for most remote sensing applications. Synergetic use to pixel based or statistical signal processing methods explores the rich information contents.

Here, we explain principle strategies of object-oriented analysis, discuss how the combination with fuzzy methods allows implementing expert knowledge and describe a representative example for the proposed workflow from remote sensing imagery to GIS.

The strategies are demonstrated using the first object-oriented image analysis software on the market, eCognition, which provides an appropriate link between remote sensing imagery and GIS.

KEY WORDS

Object-oriented image analysis, Remote sensing, multi-resolution segmentation, fuzzy classification, GIS

1. INTRODUCTION

Remote sensing imagery of a large variety of spaceborne and airborne sensor provides a huge amount of data about our earth surface for global and detailed analysis, change detection and monitoring. Powerful signal processing methods are developed to explore the hidden information in advanced sensor data [12][21][47][50][53], e.g. for hyperspectral or high-resolution polarimetric SAR data [11][12].

However, all these algorithms suffer from the problem that no contextual information can be taken into account and aggregation of information from different resources is not very well supported.

Additionally, results are mostly presented in raster format and are not well suited to incorporate into vector based geo-information-systems.

Thus there is a large gap between theoretically available information in remote sensing imagery and extracted and used information to support decision-making process in geomatics.

We propose a new strategy to bridge this gap.

Our approach focuses on

- the extension of the signal processing approach for image analysis by exploration of a hierarchical image object network to represent the strongly linked real world objects.
- usage of polygons for suitable interface to GIS (e.g. with .shp files to ArcView)
- fuzzy systems for improved and robust modeling of real world dependencies and detailed quality check of information product
- sensor and information fusion to use all available synergies

In the following we describe basic concepts of our approach, where some parts are taken from eCognition's UserGuide [56] explain some examples and discuss the enhanced possibilities due to the fuzzy classification.

1 Overview: Move from data analysis to image understanding using an hierarchical object network

In contrast to traditional image processing methods, the basic processing units of object oriented image analysis are image objects or segments, and not single pixels. Even the classification acts on image objects. One motivation for the object-oriented approach is the fact that the expected result of many image analysis tasks is the extraction of real world objects, proper in shape and proper in classification rather than single pixel classification. This expectation cannot be fulfilled by common, pixel-based approaches.

Since at least two decades processing power of affordable computers allows image processing and image segmentation. First major advantages of object-oriented analysis were derived in studies for sea-ice analysis [13], object-oriented image matching [22] and certain approaches for data compaction [18].

The first general object-oriented image analysis software on the market was eCognition [56]. This software product was produced by DEFINIENS. Although eCognition is of course a specific combination of different contributing procedures, there are some basic characteristic aspects of the underlying object oriented approach, independent of the particular methods.

Directly connected to the representation of image information by means of objects is the *networking of these image objects*. Whereas the topological relation of single, adjacent pixels is given implicitly by the raster, the association of adjacent image objects must be explicitly worked out, in order to address neighbor objects. In consequence, the resulting topological network has a big advantage as it allows the efficient propagation of many different kinds of relational information.

Each classification task addresses a certain scale. Thus, it is important that the *average resolution of image objects can be adapted to the scale of interest*. Image information can be represented in different scales based on the average size of image objects. The same imagery can be segmented into smaller or larger objects, with considerable impact on practically all information, which can be derived from image objects. Thus, specific scale information is accessible.

Furthermore, it is possible to represent image information in *different scales simultaneously* by different object layers. Bringing different object layers in relation to each other can contribute to the extraction of further valuable information.

This can be achieved, for instance, by a hierarchical networking and representation of image objects. Besides its neighbors, each object also knows its sub-objects and super-objects in such a strict hierarchical structure. This allows precise analysis of the substructures of a specific region. Furthermore, based on sub-objects, the shape of super-objects can be changed.

Image analyses can be separated in two steps, sensor specific analysis of object primitives and scene specific analysis based on the detected and recognized object primitives.

This decoupling makes image analysis very flexible. Remote sensing experts develop sensor specific methods to extract certain kinds of objects primitives from sensor data, e.g. trees for buildings. This information is available in object features and attributes and can be combined in the subsequent scene dependent processing:

As soon as trees or buildings are identified, general knowledge can be applied, e.g. the expert knowledge of a forester, who does no more need to have specific remote sensing knowledge.

That means in principal everything, which is done from that moment, an object primitive is identified as part of a tree or tree, this object and its networked environment can be analyses with a *forest* logic. Instead of processing all areas of an image with the same algorithms, a differentiated procedure can be much more appropriate, very similar to the different experts in manual image interpretation: The special knowledge of urban planners or forest engineers is used for the dedicated analysis tasks to get appropriate results. To enable this *localized usage of expert algorithms* is a specific strength of object oriented image analysis.

Characteristic for the object oriented approach is, finally, a circular interplay between processing and classifying image objects. Based on segmentation, scale and shape of image objects, specific information is available for classification. In turn, based on classification, specific processing algorithms can be activated for subsequent segmentation and to refine classification and object creation. In many applications the desired geoinformation and objects of interest are extracted step by step, by iterative loops of classifying and processing. Thereby, image objects as processing units can continuously change their shape, classification and mutual relations.

Similar to human image understanding processes, this kind of circular processing results in a sequence of intermediate states, with an increasing differentiation of classification and an increasing abstraction of the original image information. On each step of abstraction, new information and new knowledge is generated and can be used beneficially for the next analysis step. Thereby, the abstraction not only concerns shape and size of image objects, but also their semantics. It is interesting that the result of such a circular process is by far not only a spatial aggregation of pixels to image regions, but also a spatial and semantic structuring of the image's content. Whereas the first steps are more data driven, more and more knowledge and semantic differentiation can be applied in later steps. The resulting network of classified image objects can be seen as a spatial, semantic network. The image analysis basing on a hierarchical object network leads from pure data analysis to scene understanding.

2 KNOWLEDGE BASED IMAGE INTERPRETATION

The design of successful image analysis methods requires knowledge about the underlying processes. The better the knowledge about the process and the better this knowledge can be implemented in the system, the more useful the extracted information will be.

Main characteristics of the process are

1) understanding of the sensor characteristics

2) understanding of appropriate analysis scales and their combination
3) identification of typical context and hierarchical dependencies
4) considering inherent uncertainties of the whole information extracting systems, starting with the sensor, up to vague concepts for the requested information.

There a numerous publications on methods with regard to appropriate analysis of sensor data with signal processing or statistical methods (item 1 of the above list). Here, we focus on the possibilities of the object-oriented approach and fuzzy analysis of the object network to enable implementation of knowledge about items 2,3 and 4.

2.1 SELECTION AND COMBINATIONS OF SCALES

Scale is a crucial aspect of image understanding. Although in the domain of remote sensing a certain scale is always presumed by pixel resolution, the desired objects of interest often have their own inherent scale. Scale determines the occurrence or nonoccurrence of a certain object class. The same type of objects appears differently at different scales. Vice versa, the classification task and the respective objects of interest directly determine a particular scale of interest.

There is an important difference between scale and resolution: as resolution commonly expresses the average size of area a pixel covers on the ground, scale describes the magnitude or the level of abstraction on which a certain phenomenon can be described. Thus, studying an image from different levels of scale instead of an analysis approach based on different resolutions is an adequate approach to understand relations within an image and interpret the scene more easily.

The following describes the multi-scale concept for analysis of an image with depicts an urban area, e.g. by high-resolution satellite sensor as Ikonos.

Looking from a close distance on the image, one can detect and recognize single houses, buildings, roads and other urban objects. If one enlarges the viewing distance, one cannot discover single buildings, but rather different settlement types or even quarters. These areas typically can be distinguished by different textures and by different size and shape, too. The quarter's texture comprises its objects and structures on a smaller scale—houses, roads, gardens etc.—and it is especially determined by their tone, shape, and also by their topological relationships.

At a larger distance one might discover the city area as a one single entity and some surrounding agricultural areas and / or forests.

This example describes a 3 scale level approach:

1) trees, buildings and roads
2) groups of trees and groups of buildings aggregated to different settlement types
3) forest and urban area

Between these scales there is a hierarchical dependency. abstracting houses, buildings, roads and other objects, one obtains settlement areas or even quarters. The aggregation of several settlement areas yields a town. Ecosystems show analogous patterns: combining several trees builds a group of trees and combining more trees or groups of trees builds a forest. Forests and towns have a similar abstraction level. Both are of comparable scale and both are of high semantic abstraction. The hierarchical scale dependencies between the affected object classes are obvious: quarters are substructures of cities, and houses are substructures of quarters.

These hierarchical scale dependencies are implicitly self-evident in each observation and description of real world structures. However, reflecting, and especially explicit representation of these patterns adds valuable information to automated image understanding methods.

Houses in an urban area can be treated in a different way than single houses in forests, for instance; different characteristics are of interest. Thus, in order to analyze an image successfully it is necessary to represent its content on several scales simultaneously and to explore the hierarchical scale dependencies among the resulting objects.

It is obvious that these relationships and dependencies cannot be analyzed by just changing the resolution of the imagery. This would, moreover, lead to the loss of a lot of useful information.

2.2 IMAGE SEMANTICS - MUTUAL RELATIONS BETWEEN IMAGE OBJECTS

One of the most important aspects of understanding imagery is information about context. There are two types of contextual information: global context, which describes the situation of the image—basically, time, sensor and location—and local context, which describes the mutual relationships or the mutual meaning of image regions. It is obvious that the processing of context information is always consciously or subconsciously present in human perception and contributes essentially to its great capabilities.

In order to receive meaningful context information, image regions of the right scale must be brought into relation. This scale is given by the combination of classification task and the resolution of the image data. Imagine for instance the classification task to identify parks in very high-resolution imagery. A park is always a large, contiguous vegetated area. This different scale distinguishes parks from gardens. Additionally, parks are distinguished from pastures, for example by their embedding in urban areas. Single neighboring buildings are not a sufficient condition to describe parks. However, their neighborhood to single buildings is a suitable criterion for distinguishing gardens from pasture.

This simple example already shows how much the available context information depends on the scale of the structures, which are brought into relation. This astonishing fact explains why it is so difficult or even impossible to describe meaningful context relations using pixel-based approaches. Only representing image information based on image objects of the appropriate scale enables one to handle image semantics. Additionally, in order to make image objects aware of their spatial context it is necessary to link them. Thus, a topological network is created.

This network becomes hierarchical when image objects of different scale at the same location are linked. Now each object knows its neighbors, its sub- and super-objects. This additionally allows a description of hierarchical scale dependencies. Together with classification and mutual dependencies between objects and classes, such a network can be seen as a spatial semantic network.

The fact that image understanding always means dealing with image semantics was until now not sufficiently covered by the capacity of digital image analysis, especially in the field of remote sensing.

2.3 INHERENT UNCERTAINTIES AND VAGUENESS

Various types of uncertainty influence information extraction from remote sensing data. First of all, there are many factors which influence the processes of data acquisition, data processing and image generation, and which differ from scene to scene, even if the data comes from the same sensor. A very basic, inherent problem of earth observation data is that land cover can look different, depending on the season, time of day, light conditions and weather. Furthermore, the same type of objects appears highly differently depending on the sensor type, sensing geometry and the resolution.

The dependency between features and land cover or land use is mostly only roughly modeled and vagueness is inherent even in the concepts of land cover and land use. Sensor measurements—the basic source for image pixels—have limited radiometric resolution even after careful calibration of the instrument. The geometric resolution in remote sensing—and in any data acquisition process—is limited as well. This effect leads to class mixture within one resolution cell: if a resolution cell covers water-land transition, the relevant pixel represents to some degree water and to some degree the land cover of the shore area.

The image generation process converts sensor measurements to image data. Additionally, these data have to be compressed to reduce requirements for archiving and data transmission. In most cases, these data processing steps cause artifacts and ambiguities, which lead to noise and therefore to additional uncertainty in the final image data.

Usually only vague concepts exist for land cover and land use. There is no exact threshold between densely and sparsely populated area, or between low and high vegetation. Whenever thresholds are defined in terms of numbers, they are mostly unsatisfactory idealizations of the real world and therefore subsequently lead to problems during classification and performance estimation of the classification.

Information retrieval from remote sensing databases is based to a large extent on vague knowledge. Especially important context information is typically only expressed in terms of vague linguistic rules. For example, if trees are "nearly completely" surrounded by urban area, they are assigned to the class *park*.

Furthermore, in many cases the desired information for a specific classification task is not, or not sufficiently, contained in the available image data. This can be caused by spatial or radiometric resolution, because the signal to noise ratio is too low, or simply because the sensor does not deliver unambiguous signal for the desired class separation.

If these uncertainties are not taken into account in information extraction, classification will not be robust and transferable. There are several approaches, so called soft classifiers, which take these uncertainties into account. One of the most powerful soft classifiers are fuzzy classification systems, which are able to incorporate in the analysis approach from the very beginning on inaccurate sensor measurements, vague class descriptions and unprecise modeling. Degree of uncertainty is part of the fuzzy classification result [3][5][6][37][56].

3 IMAGE OBJECTS

The basic elements of an object-oriented approach are of coarse image objects. Image objects describe certain contiguous regions in an image. We distinguish between image objects primitives and objects of interest. Only object of interest match real world object, e.g. the building footprints or whole agricultural parcels. Object primitives are usually the necessary intermediate step before objects of interest can be found by segmentation and classification process. The smallest image object is one pixel.

Image objects can be linked to a hierarchical network, where they carry a high-dimensional feature space:

Image object statistics and texture

Within an image object all kind of *statistics* based on single input layers or combinations within the input image layer stack can be computed, e.g. the mean value of the ratio of two input channels *A* and *B*.

$$f_{r\_AB} = \frac{\frac{1}{n}\sum_{n} p_A(x_n)}{\frac{1}{n}\sum_{n} p_B(x_n)}$$

with n number of pixels x within object; $p(x)$ value of pixel at location x.

Using image objects to calculate this statistic instead of boxes of pixels allows reliable statistic without smearing edges, since objects do not exceed edges.

Image object shape

The closer objects primitives are to objects of interest, the more image object shape features can be used as additional uncorrelated object features. Since they are usually independent from sensor characteristics they are robust versus sensor calibration and illumination conditions.

Typical examples are area of objects, their length-to-width ratio, number of straight borders and many more. Advanced shape features can be derived from object polygons and object skeletons, the latter describing the inner structure of an object.

Image objects statistics, texture (e.g. Haralick features [20]), shape can be regarded as intrinsic features. They are available for each object.

Topological object features

Due to the object network context features are provided. Within one scale relations to neighbored objects can be evaluated, whereby the size of the neighborhood can be defined as parameter. Between image scales hierarchical relations can be explored, where the distance of scales can be adjusted using distance scale parameter.

This hierarchical object network enables addressing of context and semantic for subsequent image analysis with innovative techniques:

The hierarchical network provides additional object features:

- *Characterization of an image object based on its sub-objects using*
    a. Texture analysis based on sub-objects, classifying attributes of all sub-objects of an image object on average. Attributes can for instance be contrast or shape.
    b. Line analysis based on sub-objects.
    c. Class-related features: relationships to classified sub-objects, such as the relative area of other image objects assigned to a certain class, e.g. if an urban area on higher level contains many sub-objects classified as houses, this urban area can be described as dense vs. other less dense areas.

Characterization of an image object based on its super-objects, e.g. houses belonging to a super object urban can be classified as urban houses, whereas houses in rural areas can be classified as cottages or special buildings.

Semantic features

These higher order features are available after a first classification of image objects. They allow describing a park as forested region within urban area or shore regions as adjacent land regions to water. These very features are important for advanced remote sensing image analysis. The reduce ambiguities, allow land use classification in addition to pure land cover classification and thus lead to a first step of scene understanding

In the following we describe image object creation process.

3.1 CREATION OF IMAGE OBJECTS

Objects are created by image segmentation, which is the subdivision of an image into separated regions. Image segmentation is a long year research topic in the area of image analysis [25][35][36][46]. In almost all cases, segmentation is an optimization process. Regions of minimum heterogeneity given certain constraints have to be found. Criteria for heterogeneity, definition of constraints and strategy for sequence of aggregation determine the final segmentation result.

Heterogeneity can refer to *primary object features*, such as standard deviation or gray tones, shape of object, or texture on objects or on *higher order object features*, such as class assignment of objects. Segmentation methods using heterogeneity definition relying only on primary object features can usually only deliver object primitives, without a direct relationship to real world objects. However, these object primitives can be assigned to classes during a first classification step and then the higher order object feature "class assignment" is available for classification based segmentation [45]. This advanced segmentation step is able to create objects of interest with unique relation to the depicted real world.

Segmentation in eCognition ([1][2]) allows as well segmentation based on primary features (gray tone and shape) and – after an initial classification - the more advanced classification based segmentation. The method leads for most data distributions to robust results and is applicable under many conditions. Constraints can be used to ensure exact reproducibility of segmentation.

As already mentioned in the chapter 2.1 image scale is very important for meaningful analysis. Therefore eCognition provides segmentation on several scales. Scale selection is performed using certain parameters.

Details to eCognition's object creation approach are provided in the following chapters.

3.1.1 OBJECT CREATION IN ECOGNITION

eCognition's multi-resolution segmentation is a bottom up region-merging technique starting with one-pixel objects. In numerous subsequent steps, smaller image objects are merged into bigger ones. Throughout this pairwise clustering process, the underlying optimization procedure minimizes the weighted heterogeneity $n \cdot h$ 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, multi-resolution segmentation is a local optimization procedure.

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.

To ensure reproducibility on same image, constraints can be used to force an exact reproducible segmentation. Here a global optimization criterion is used.

3.1.1.1 DEFINITION OF HETEROGENEITY

Heterogeneity in eCognition considers as primary object features color and shape. For fusion decision not the heterogeneity itself is important, but the increase of heterogeneity. This increase has to be less than a certain threshold.

$$f = w_{color} \cdot \Delta h_{color} + w_{shape} \cdot \Delta h_{shape},$$
$$w_{color} \in [0,1,], w_{shape} \in [0,1,]$$
$$w_{color} + w_{shape} = 1$$

The weight parameters allow to adapt heterogeneity definition to the application.

The spectral heterogeneity allows multi-variate segmentation giving to the image channels c certain weight w_c. Difference spectral heterogeneity is defined as following.

$$\Delta h_{color} = \sum_c w_c \left(n_{merge} \cdot \sigma_{c,merge} - \left(n_{obj\_1} \cdot \sigma_{c,obj\_1} + n_{obj\_2} \cdot \sigma_{c,obj\_2} \right) \right)$$

with n_{merge} number of pixels within merged object, n_{obj_1} number of pixels in object 1, n_{obj_2} number of pixels in object 2, σ_c standard deviation within object of channel c. Subscripts *merge*, *obj_1* and *obj_2* refer to the merged object, object 1 and object 2 prior to merge, respectively.

The shape heterogeneity is a value that describes the improvement of the shape with regard to smoothness and compactness of object's shape.

$$\Delta h_{shape} = w_{compct} \cdot \Delta h_{compt} + w_{smooth} \cdot \Delta h_{smooth}$$

with

$$\Delta h_{smooth} = n_{merge} \cdot \frac{l_{merge}}{b_{merge}} - \left(n_{obj\_1} \cdot \frac{l_{obj\_1}}{b_{obj\_1}} + n_{obj\_2} \cdot \frac{l_{obj\_2}}{b_{obj\_2}} \right)$$

$$\Delta h_{cmpct} = n_{merge} \cdot \frac{l_{merge}}{\sqrt{n_{merge}}} - \left(n_{obj\_1} \cdot \frac{l_{obj\_1}}{\sqrt{n_{obj\_1}}} + n_{obj\_2} \cdot \frac{l_{obj\_2}}{\sqrt{n_{obj\_}}} \right)$$

with n_{merge} number of pixels within merged object, n_{obj_1} number of pixels in object 1, n_{obj_2} number of pixels in object 2, l_{merge} perimeter of merged object, l_{obj_1} perimeter of object 1, l_{obj_2} perimeter of object 2, b_{merge} perimeter of the merged object's bounding box, b_{obj_1} perimeter of object 1 bounding box, b_{obj_2} perimeter of object 2 bounding box.

Thus, the smoothness heterogeneity equals 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.

The compactness heterogeneity equals the ratio of the de facto border length l and the square root of the number of pixels forming this image object.

The weights $w_c, w_{color}, w_{shape}, w_{smooth}, w_{cmpt}$ are parameters, which can be selected in order to get for a certain image data stack and a considered application suitable segmentation results.

The scale parameter is the stop criterion for optimization process. Prior to the fusion of two adjacent objects, the resulting increase of heterogeneity f is calculated. If this resulting increase would exceed a threshold t determined by the scale parameter, $t = \Psi(scale)$ then no fusion takes place and segmentation stops.

$$f > \Psi(scale) \quad \textit{then} \quad \textit{segment fusion} \quad \textit{is} \quad \textit{discarded}$$
$$f \le \Psi(scale) \quad \textit{then} \quad \textit{segment fusion} \quad \textit{takes} \quad \textit{place}$$

If no more objects can be fused according to this constraint, segmentation stops.

The larger the scale parameter, the more objects can be fused and the larger the objects grow. Details are to be found in [2].

Figure 1: Exemplary segmentation result in eCognition

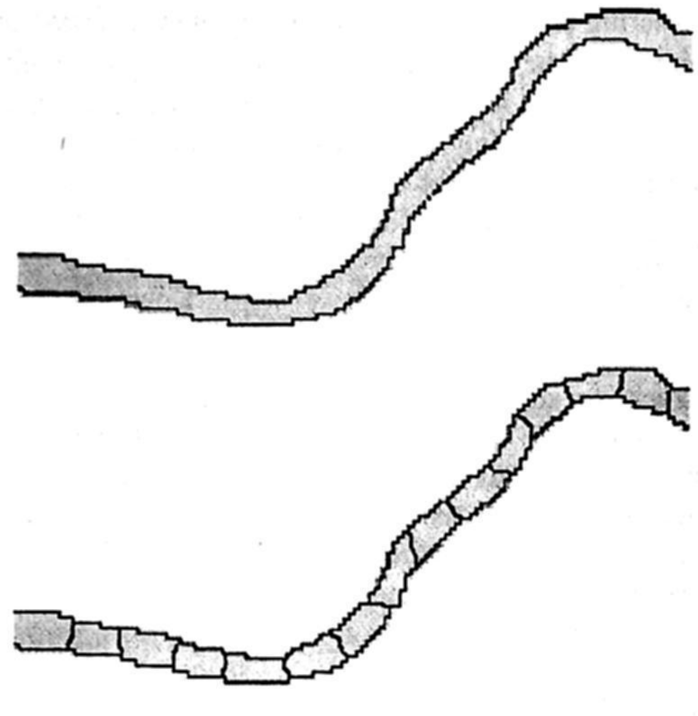


Figure 2: Linear structure subsegmented into compact objects

3.1.1.2 ALTERNATIVE CREATION MODES IN ECOGNITION FOR OBJECT PRIMITIVES

Appropriate object creation with respect to different applications may require alternative approaches to the described standard implementation in eCognition. Therefore external segmentation results can be inserted into eCognition, e.g. using thematic layers on in the latest version of eCognition alternative methods are available.

Segmentation according to the spectral difference of objects

Using the mode "spectral difference" large homogeneous areas can be created regarding spectral difference. Areas, which have a lower spectral difference than a certain threshold are merged. The scale parameter determines the threshold of the spectral difference of neighboring objects, below which they are merged.

Segmentation of sub-objects for the purpose of line analysis

Object oriented line analysis of image objects can be performed using a special mode of segmentation, which is available due to the object hierarchy. This mode uses only heterogeneity compactness. The scale parameter—here ranging from 0.5 to 1—determines the maximum relative border length of sub-objects to neighbors, which are not sub-objects of the same superior object.

For the analysis of image objects such as in **Figure 2** the specific image object level can be sub-segmented. The results are compact sub-objects, which guarantee a minimum and maximum border length to the outer environment. Operating from center point to center point of these sub-objects means that it is possible to easily analyze the length of a curved line, average thickness, curvature etc.

3.1.2 VALIDATION OF OBJECT CREATION PROCESS

Human interpretation and correction: Automatic segmentation replaces in the usual image interpretation workflow manual digitizing of polygons. Thus a strong and experienced source for the evaluation of segmentation techniques is of course the human expert. It can't be expected that automatic segmentation result will be fully convincing for human interpreter. Therefore, eCognition provides also possible manual interaction (manual section and manual fusion) to use automatic segmentation for the major segmentation part of the image and support subsequent correction by a human expert for small areas.

Automatic validation: There are several approaches to evaluate segmentation quality.

a. Reference polygons (e.g. provided by manual digitizing) can be used to test the automatic segmentation. If the complete reference polygons is covered by automatically achieved segments, best scores are given,
    - if minimum number of segments are within the reference segment (lowest possible over segmentation)
    - if minimum area of segments outside of reference polygon is covered
b. Strength of segment borders is analyzed. The higher the border between to segments, the less probable is their merging in the optimization process. Thus even certain variations of parameters or conditions will not change the segmentation result. Thus, the larger the number of strong borders relative to weak borders in an segmented image, the more stable and reproducible the segmentation will be for similar scenarios.

c) reproducible the segmentation will be for similar scenarios.

3.2 HIERARCHICAL OBJECT NETWORK

Object creation is a complex and very often time-consuming process. However, it is in many cases of significant advantage for image analysis and geo-information production.

Objects carry much more information than single pixels or boxes of pixels do, and thus allow image analysis with higher accuracy. One example, in object-oriented analysis "rivers" can be distinguished from "lakes" by the different shape of these objects. This huge uncorrelated object feature space enables robust classification.

Linking objects to a hierarchical network provides further advantages.

3.2.1 HIERARCHICAL NETWORK CREATION IN ECOGNITION.

The different levels of image objects are generated by the described multi-resolution segmentation. In general, the higher the level and the larger the average size of image objects, the larger was the chosen scale parameter.

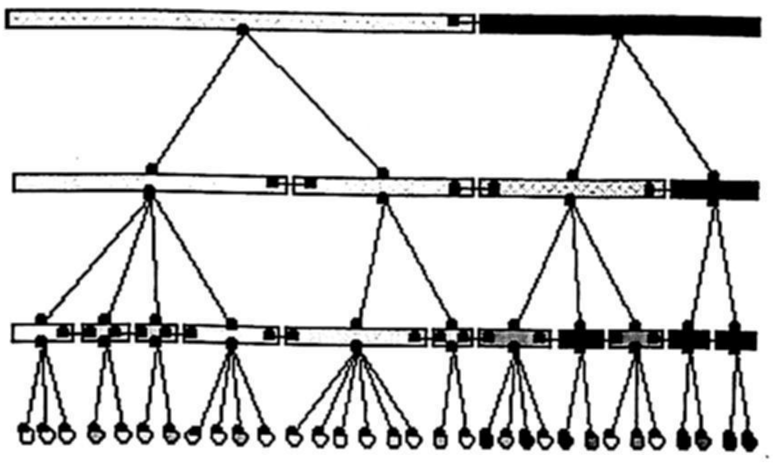


Figure 1: 4 level hierarchical network of image objects in abstract illustration

All segmentation procedures provided by eCognition operate on arbitrary levels in a strong hierarchical network. Since the level of pixels and the level of the whole image always exist by definition, each segmentation of a new level is a construction in between a lower and an upper level. To guarantee a definite hierarchy over the spatial shape of all objects the segmentation procedures follow two rules:

- Object borders must follow borders of objects on the next lower level.
- Segmentation is constrained by the border of the object on the next upper level.

Within eCognition

- *Structures of different scales can be represented simultaneously* and thus classified in relation to each other.
- *Different hierarchical levels can be segmented based on different data*; an upper layer, for instance can be built based on thematic land register information, whereas a lower layer is segmented using remote sensing data. Classifying the upper level, each land register object can be analyzed based on the composition of its classified sub-objects. By means of this technique different data types can be analyzed in relation to each other.
- *Object shape correction* based on regrouping of sub-objects is possible

This network provides the bases for most powerful information extraction, because many successful strategies of human analyst can be approximated:Relations between scales and combinations of scales can be used, e.g. one could look based on the same image on trees, on groups of trees and on forest. Roads (extracted on low scale) leading through forest areas (extracted on high scale) can be classified as *forest roads*. Based on the width of the roads certain drivability can be assigned as feature in the output for a geo-information system. Furthermore, context information and semantic can be used to distinguish between trees within a forest or within an urban area.

3.3 CREATION OF VECTOR INFORMATION TO BRIDGE REMOTE SENSING AND GEO-INFORMATION SYSTEMS

Image objects not only enhance automatic classification of remote sensing imagery, they support also export of the extracted information to geo-information systems, since they can be easily converted to polygons using vectorization approaches. Within eCognition this vector structures are not only used for import and export, but also for advanced classification.

eCognition supports a simultaneous raster / vector representation of image objects. After segmentation, vectorization functionality allows production of polygons and skeletons for each image object. This vector information is produced in different resolutions for different purposes.

eCognition produces polygons along the pixel raster (**Figure 4**: polygons 1) or slightly abstracted polygons (**Figure 4**: polygons 2). The latter polygons are referred to in the following as base polygons. They are created with respect to the topological structure of image objects and are used for exporting vector information, too. More abstracted vector information represents the shape of image objects independently of the topological structure (**Figure 4**: polygons 3) and is used for the computation of shape features. Theses polygons are referred to as shape polygons.

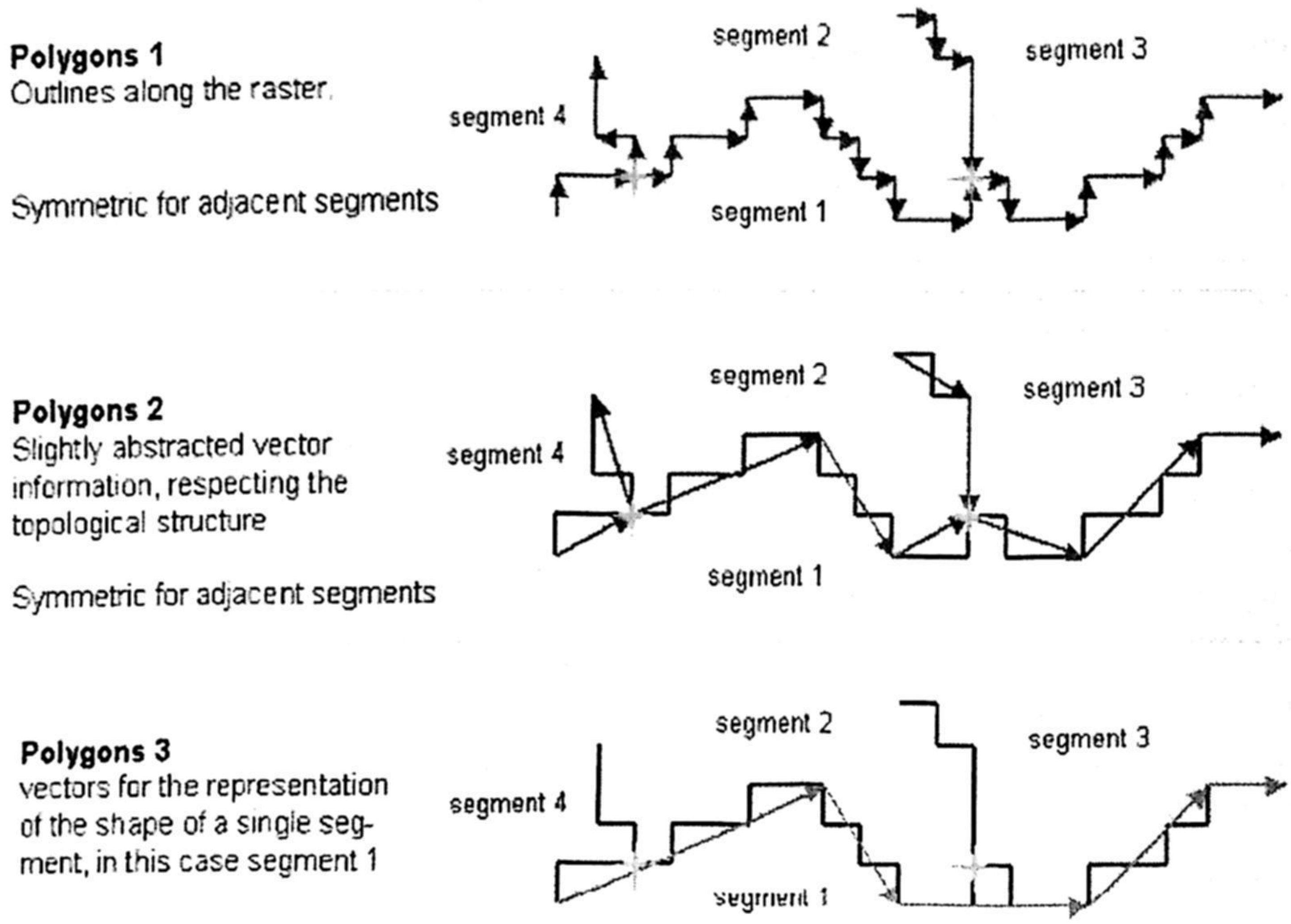


Figure 4: Different polygon types for the vectorization of segments /image objects.

The computation of base polygons is done by means of a Douglas Peucker [15] algorithm. The Douglas Peucker algorithm is one of the most common procedures for polygon extraction. It is a top-down approach, which starts with a given polygon line and divides it into smaller sections iteratively.

1. Given the two end points of a polygon line—in eCognition typically these two starting points are topological points, see yellow marks in Figure—the algorithm detects this specific point on the polygon line with the largest vertical distance to a line connecting the two end points, see Figure.
2. At this detected point, the polygon line is cut into two shorter polygon lines, **Figure 5**b.
3. This procedure continues until the longest vertical distance is smaller than a given threshold, **Figure 5c.**

In other words: the threshold describes the strongest possible deviation of the polygon from the underlying raster. In eCognition, this threshold can be interactively defined to meet the needs of the application and is measured in pixel units.

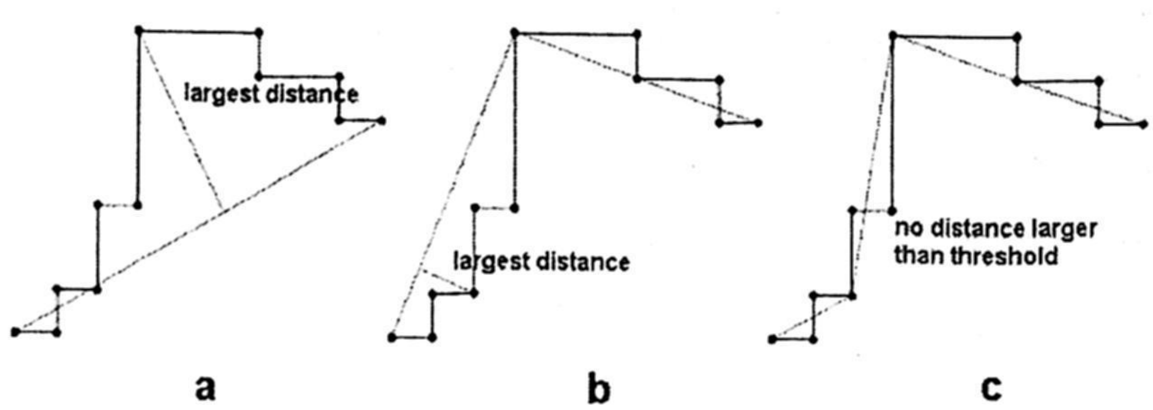


Figure 5: Douglas-Peucker algorithm: a) start configuration and detection of largest distance; b) new state after dividing into two sections; c) final result, no further division as no distance is larger than given threshold

The Douglas-Peucker algorithm in its pure application suffers in some cases in producing relatively acute angles. In order to improve the result, in eCognition angles smaller than 45 degrees are detected in a second run. From the two particular vectors at such an angle, that one is subdivided which will result in the largest angles. This procedure continues in iterative steps until there are no angles smaller than 45 degrees.

For high thresholds, which produce a strong abstraction from the original raster, slivers and intersections within and between base polygons can arise. This can be especially disturbing when these base polygons are used for export. In order to avoid this effect, an additional, optional algorithm detects intersections and fractionates the affected vectors.

The *shape polygons* are created by means of a derivative of multiresolution segmentation (3), in this case not applied to image regions but to single vectors. In contrast to the Douglas-Peucker algorithm this procedure is a bottom-up approach. Starting with base polygons, the single vectors are subsequently merged, optimizing a homogeneity criterion. It is important to understand that the heterogeneity of single shape vectors is defined as deviation of the underlying base vectors. Thus, a threshold of 0 will always produce shape polygons identical with the underlying base polygons. The resulting shape therefore depends also on the threshold of the base polygons. A threshold bigger then 0 will result in a stronger abstraction than the base polygons. Concretely, the deviation is computed as the maximum of the difference of length between shape vector and underlying base vectors and the sum of the lengths of the vertical parts of the underlying base vectors to the shape vector. Iteratively, the two adjacent vectors of a polygon, which result in the smallest heterogeneity, are merged. This continues until the predefined threshold is reached.

3.3.1 OBJECT FEATURES BASED ON POLYGONS

The resulting shape polygons are independent of the topological structure and therefore specific for each single image object. A straight edge of a segment is represented as one vector, even if it contains a topological point

Thus, fractal parts of the boundary of an image object are represented in a characteristic way by a number of short vectors, whereas straight edges are represented by long edges. Based on these shape polygons meaningful shape features can be computed, e.g. the number of straight edges, average length of edges and maximum length of edges: Artificial targets are usually characterized by few long straight edges, whereas natural targets are more irregularly shaped.

Skeletons are advanced object features based on polygons. They describe the inner structure of an object, which provides new characteristics for an image object.

They provide centerline of objects and second and higher order branches. Thus instead of the street detected in remote sensing imagery just the center line of the street can be exported and later on by appropriate map production software assigned with the width of its importance and according to the defined map scale.

Skeletons then are created by identifying the mid points of the triangles in an image object and connecting them. Thereby the triangles' mid points are determined by connecting the midpoints of the triangles' sides.

To find skeleton branches, three types of triangles are created: branch-triangles (three-neighbor-triangle), connecting triangles (two-neighbor-triangles) and end-triangles (one-neighbor-triangles).

- Branch triangles indicate branch-points of the skeleton,
- two-neighbor-triangles indicate a connection point and
- end-triangles indicate end-points of the skeleton.

To obtain the skeletons, the generated points are connected. The longest possible connection of branch-points is defined as main line.

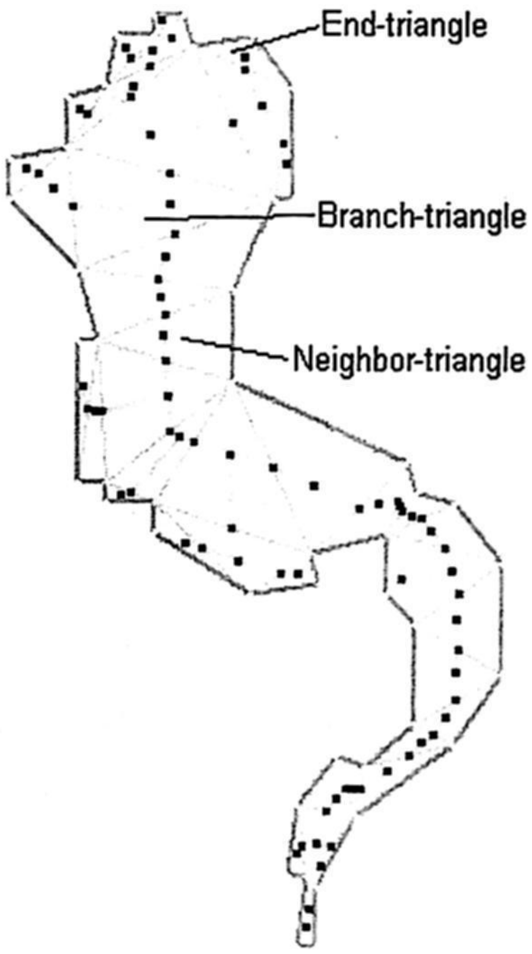


Figure 6: Creation of skeletons based upon a Delauney triangulation of image objects' shape polygons.

Skeletons describe the objects inner structure and shape in detail. Hence, they provide input for advanced automated shape correction. For example an automated object cut can be started to cut high order branches of a fractal object. Typical example is lower order streets connected to a main road. The automated object cut can be can be started to cut high order branches of a fractal object. Typical example is lower order streets connected to a main road. The automated object cut can be understood as pruning the object's skeleton from outside to inside.

3.3.2 VECTOR FORMAT IMPORT AND EXPORT

Efficient import of extracted information into geo-information systems is possible, because objects can be represented easily by polygons as shown in the previous chapter.

eCognition supports the import and export of thematic data in shape format. Since eCognition is a region based analysis system, only polygons are considered for import.

For internal usage this vector information is transformed to raster format. Export supports polygons, line and point information. While lines in vector format are based on the lines of the skeletons, points are equivalent to the center-point of the main line for each object to be exported.

4 FUZZY CLASSIFICATION

Fuzzy classification is beside neural networks [19] and probabilistic approaches [12] a very powerful soft classifier and typically represents and expert system for classification [53]. It takes into account

- uncertainty in sensor measurements
- parameter variations due to limited sensor calibration
- vague (linguistic) class descriptions
- class mixtures due to limited resolution.

Fuzzy classification consists of a n-dimensional tupel of membership degrees, which describes the degree of class assignment of the considered object *obj* to the *n* considered classes.

$$f_{class,obj} = \lfloor \mu_{class\_1}(obj), \mu_{class\_1}(obj), \ldots \mu_{class\_n}(obj) \rfloor$$

Crisp classification would only give the information, which membership degree is the highest, whereas this tupel contains all information about the overall reliability, stability and class mixture.

Fuzzy classification requires a complete fuzzy system, consisting of fuzzification of input variables resulting in fuzzy sets, fuzzy logic combinations of these fuzzy sets and defuzzification of the fuzzy classification result to get the common crisp classification for map production.

Fuzzy logic is a multi-valued logic quantifying uncertain statements. The basic idea is to replace the two Boolean logical statements "true" and "false" by the continuous range of [0...1], where 0 means "false" and 1 means "true" and all values between 0 and 1 represent a transition between true and false. Avoiding arbitrary sharp thresholds, fuzzy logic is able to approximate real world in its complexity much better than the simplifying Boolean systems do. They can take into account imprecise human thinking and can implement linguistic rules.

Hence, fuzzy classification systems are well suited to handle most sources of vagueness in remote sensing information extraction. The mentioned parameter and model uncertainties are considered by fuzzy sets, which are defined by membership functions.

Fuzzy systems consist of three main steps, fuzzification, fuzzy rule base and defuzzification, which are briefly described in the following.

4.1 FUZZIFICATION

Fuzzification describes the transition from a crisp system to a fuzzy system. It defines on an object feature certain sets, which assign for example all feature values in a certain range to a specific class, e.g. "low". The sets are defined using membership functions. They assign a membership degree between 0 and 1 to each (object) feature value with respect to the considered feature class. Depending on the shape of the function, the transition between "full member" and "no member" can be crisp (for a rectangular function) or fuzzy (see **Figure 7**, set M).

All feature values, which have a membership value higher than 0 belong to a fuzzy set. In general, the broader the membership function, the more vague the underlying concept; the lower the membership values, the more uncertain is the assignment of a certain value to the set.

Within the fuzzy system not feature values are combined but the fuzzy sets defined on these features values. Hence all calculations refer to membership degrees with the defined range between 0 and 1, independent of the dynamic of the originally crisp features. This simplifies working in a high-dimensional feature space with different dynamics and features of various types, e.g., backscatter from different sensors, geographic information, texture information and hierarchical relations.

For successful classification a deliberate choice of membership function is crucial. This is one of the most important steps to introduce expert knowledge into the system. The better the knowledge about the real system is modeled by the membership functions, the better the final classification result [9].

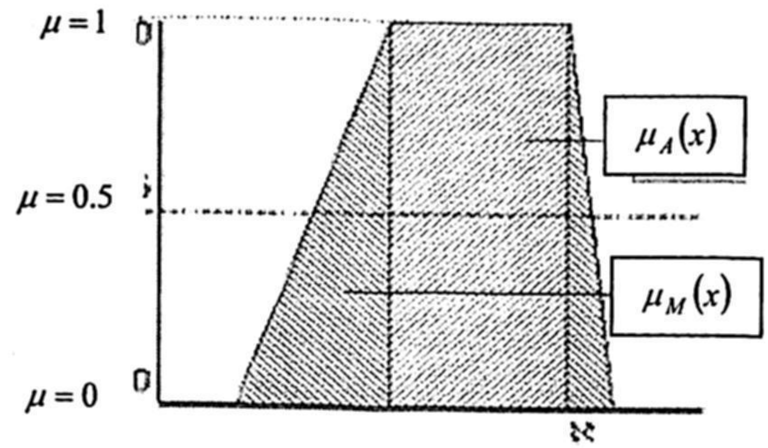


Figure 7: Rectangular and trapezoidal membership functions on feature x to define crisp set M (///), $\mu_M(x) \in \{0,1\}$ and fuzzy set A (\\\) $\mu_A(x) \in [0,1]$ over the feature range X;

It is possible to define more than one fuzzy set on one feature, e.g., to define the fuzzy sets *low*, *medium* and *high* for one object feature. The more the memberships overlap, the more objects are common in the fuzzy sets and the vaguer the final classification.

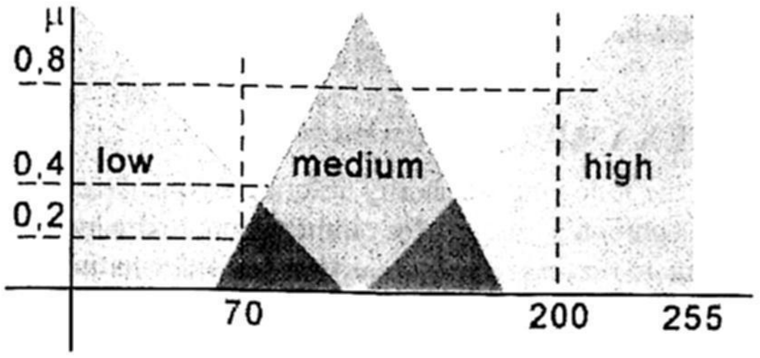


Figure 8: The membership functions on feature *x* define the fuzzy set *low*, *medium* and *high* for this feature.

Figure shows three fuzzy sets defined for the feature x: *low*, *medium* and *high*. They are characterized by overlapping triangular membership functions.

For an image object with a feature value of x = 70, the membership to class *low* is 0.4, to class *medium* is 0.2 and to class *high* is 0.0. If the feature value x equals 200, the membership to the classes is 0.0, 0.0, 0.8, respectively.

4.2 FUZZY RULE BASE

A fuzzy rule base is a combination of fuzzy rules, which combine different fuzzy sets. The simplest fuzzy rules are dependent on only one fuzzy set.

Fuzzy rules are "if – then" rules. If a condition is fulfilled, an action takes place. The following rule could be defined: "If" feature x is low, "then" the image object should be assigned to land cover *W*. In fuzzy terminology this would be written: If feature x is a member of fuzzy set *low*, then the image object is a member of land cover *W*. According to the definition in **Figure 8**, in case feature value x = 70, the membership to land cover *W* would be 0.4, in case x = 200, the membership to land cover *W* would be 0.

To create advanced fuzzy rules, fuzzy sets can be combined. An operator returns a fuzzy value that is derived from the combined fuzzy sets. How this value is derived depends on the operator. The logic operators are "and", "or" and "not". There are several possibilities to realize these operators. In most cases the simplest implementation is to use minimum operation to implement the fuzzy "and" and the maximum operation to implement fuzzy "or".

The results are very transparent and ensure independence of the sequence of logic combinations within the rule base (A "and" B gives the same result as B "and" A). In addition a hierarchic structure following common logic (e.g., A "or" (B "and" C) equals (A "or" B) "and" (A "or" C)) can be created easily.

A fuzzy rule base delivers a fuzzy classification, which consists of discrete return values for each of the considered output classes (see **Figure 9**). These values represent the degree of class assignment.

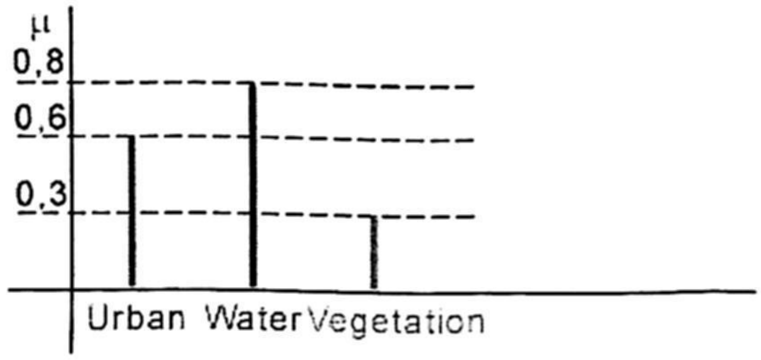


Figure 9: Fuzzy classification for the considered land cover classes urban, water and vegetation. The image object is a member of all classes to various degrees

$\mu_{urban}(obj) = 0.6, \mu_{water}(obj) = 0.8, \mu_{vegetation}(obj) = 0.3$

Please consider that fuzzy classification gives a possibility for an object to belong to a class, while classification based on probability provides a probability to belong to a class. A possibility gives information on a distinct object. Probability relies on statistics and gives information on many objects. Whereas the probability of all possible events adds up to one, this is not necessarily true for possibilities.

The higher the membership degree for the most possible class, the more reliable is the assignment. In the example above, the membership to water $\mu_{water}(obj) = 0.8$ is rather high and in most applications this object would therefore be assigned to the class *Water*. The bigger the difference between highest and second highest membership value, the clearer and more stable the application. Classification stability and reliability can be calculated and visualized within eCognition as an advanced method for classification validation.

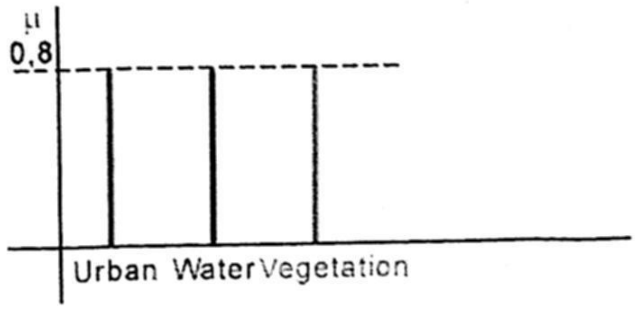


Figure 10: Fuzzy classification for the considered land cover classes *Urban, Water* and *Vegetation.*

In figure 10 the equal membership degrees indicate an unstable classification between these classes for the considered image object and can be a description of class mixture within the resolution cell or that class definition is not sufficient to distinguish between the classes. If the land cover classes can be distinguished on the data set for other objects, class mixture is very probable.

The high membership

$$\mu_{urban}(obj) = \mu_{water}(obj) = \mu_{vegetation}(obj) = 0.8$$

value shows that the assignment to this class mixture is reliable.

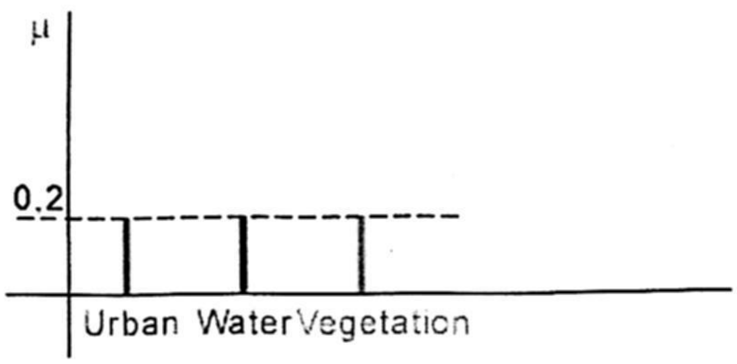


Figure 11: Fuzzy classification for the considered land cover classes *Urban, Water* and *Vegetation.*

The equal membership degrees in figure 11 again indicate an unstable classification between these classes for the considered image object, as in figure 10. However, the low membership value

$$\mu_{urban}(obj) = \mu_{water}(obj) = \mu_{vegetation}(obj) = 0.2$$

indicates a highly unreliable assignment. Assuming a threshold of a minimum membership degree of 0.3, no class assignment will be given in the final output.

This analysis of fuzzy classification provides an important input for classification validation but furthermore for information fusion in current and future remote sensing systems with multi-sensor sources and ancillary data. The reliability of class assignments for each sensor can be used to find the most possible and probable class assignment. A solution is possible, even if there are contradictory class assignments based on different sensor data, e.g., optical sensors are regarded as being less reliable than radar sensors if there is a heavy fog.

4.3 DEFUZZIFICATION

To produce results like maps for standard land cover and land use applications, the fuzzy results have to be translated back to a crisp value, which means that an object is either assigned to a class or not. For defuzzification of classification results the class with the highest membership degree is chosen.

Defuzzification is the reverse process of fuzzification. It delivers a crisp classification. If the membership degree of a class is below a certain value, no classification is performed to ensure minimum reliability.

As this output discards the rich measures of uncertainty of the fuzzy classification, this step should be the final step in the whole information extraction process.

$$f_{crisp} = \max\{\mu_{class\_1}(obj), \mu_{class\_2}(obj), \ldots, \mu_{class\_n}(obj),\}$$

with class assignment equal to the class i with the highest membership.

Further information on fuzzy systems in image analysis and remote sensing can be found in the following references [5][6][26][37].

5 EXAMPLE

In the following we shortly describe a typical example for eCognition's usage for information extraction from remote sensing imagery to update geo-information.

The goal of this example was to analyze a mosaic of high-resolution aerial orthoimages of FMM, an Austrian company. Input files were the image mosaic and shape files showing building footprints and roads. This information should be updated and extended by polygons for impervious areas.

Figure 12: Provided polygons of streets and buildings

Figure 13: Image mosaic provided by FMM Forest Mapping Management, Austria

Based on image subset, segmentation and classification strategy is developed.

- roof
- not roof
    - non impervious
    - impervious
    - probable impervious
        - could be impervious
        - not likely to be impervious
    - shadow
        - shadow on vegetation
        - shadow on impervious area

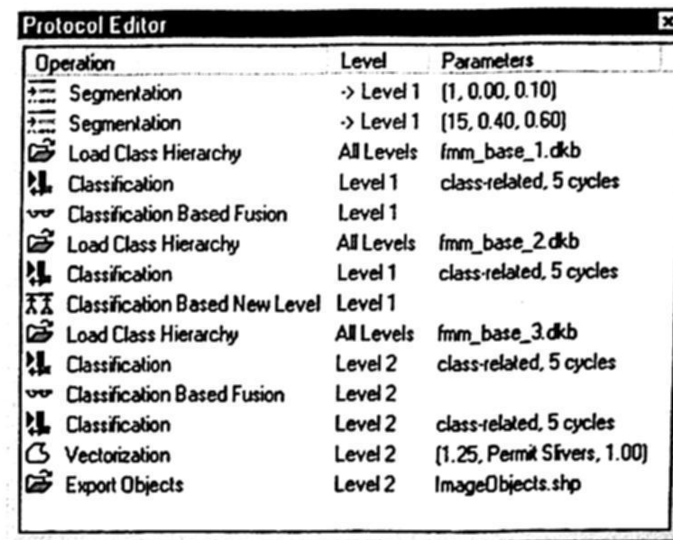
Figure 14: Hierarchical rulebase structure in eCognition

On two scale levels classification takes place. The hierarchical rule base defines on scale 1 first the classes "roof" and "not roof". "not roof is further subdivided into "non impervious", "shadow", "impervious" and probable "impervious". "Shadow is classified as "shadow over vegetation", or "shadow over impervious area".

This hierarchy in rule base design allows a well-structured incorporation of knowledge with low mutual influence of object classes.

As the class names already show, linguistic and vague concepts are necessary to take uncertainty into account. The helpful concept to use shadow for further classification is only possible using the neighborhood concept that elevated targets as buildings throw shadow.

Using protocols this developed strategy is saved in a program routine and can be applied automatically on the whole image mosaic.



Protocol Editor

Operation	Level	Parameters
Segmentation	-> Level 1	{1, 0.00, 0.10}
Segmentation	-> Level 1	{15, 0.40, 0.60}
Load Class Hierarchy	All Levels	fmm_base_1.dkb
Classification	Level 1	class-related, 5 cycles
Classification Based Fusion	Level 1	
Load Class Hierarchy	All Levels	fmm_base_2.dkb
Classification	Level 1	class-related, 5 cycles
Classification Based New Level	Level 1	
Load Class Hierarchy	All Levels	fmm_base_3.dkb
Classification	Level 2	class-related, 5 cycles
Classification Based Fusion	Level 2	
Classification	Level 2	class-related, 5 cycles
Vectorization	Level 2	{1.25, Permit Slivers, 1.00}
Export Objects	Level 2	ImageObjects.shp

Figure 15: Protocol for automatically analysis of mosaic

The protocol shows very clearly the interactive process of segmentation and classification.

Results are the

- a classification map and the reliability map. **(Figure 16)**
- and statistics with relation to certain classes and with respect to single objects **(Figure 17)**
- updated and extended shapefile **(Figure 19)**

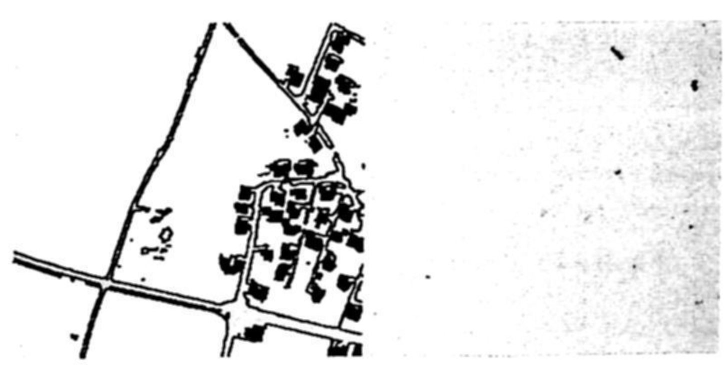


Figure 16: Classification map (left) of roads, buildings and impervious areas and reliability map (right); very bright and very dark objects in black/white presentation show less reliable classifications.

The reliability map (**Figure 16**, right) supports the semi-automatic workflow. Only those objects flagged as less reliable have to be manually assigned after inspection of the aerial images or – if no decision is possible base don the image in situ observations have to be performed.

Thus the methods do not replace all manual interactions, but reduces the amount significantly and increases objectivity to the large area of automatic classification.

Due to the final supported check by experts not only a time efficient process is possible, but also a product with high classification accuracy and reliability can be provided.

id	Best Class ID	Best Member :	Mean 102451
1	11	1	99.1171
2	12	1	101.753
3	14	1	24.5
4	14	0.978938	204.209
5	14	1	37.6667
6	14	0.991359	211.292
7	14	0.9828	221

Class	building	non imperviou:	impervious
Objects	218	91	883
Sum Area	40818	341016	121684
Mean Area	187.239	3747.42	137.807
StdDev Area	168.376	13328.6	1857.64
Min Area	1	0.25	0.25
Max Area	1667	107179	54654.8
Sum Length	3966.1	4887.51	8903.85
Mean Length	18.1931	53.7089	10.0836

Figure 17: Exemplary statistics for export.

Figure 19: Updated and extended shape file

Due to the object-oriented approach with

- the possibility to take context and semantic information into account and
- the ability for vector based input and output and
- due to the robust fuzzy classification with its advanced accuracy and reliability assessment

an operational system could be developed for analysis of aerial image mosaic and update of GIS- information.

The efficiency of the up-to-date time consuming and subjective analysis with many in-situ measurements can be improved and thus the quality of final geo-information can be increased while simultaneously reducing costs.

6 CONCLUSION

The main focus at Definiens is to produce software for the analysis of dependencies within complex systems. This can only be done if the high degree of mutual relationships and actions on different scales such as context information, semantic and hierarchical structure is taken into account. With DEFINIENS Cognition Network Technology the basis is available to analyze images and texts from many different domains, and to combine the information from heterogeneous sources to support decision-makers in geomatics and biotechnology. The product eCognition, which is based on DEFINIENS Cognition Network Technology, is applied to geomatics

There are many things to improve for workflow and to increase the synergy with signal processing approaches. However, first two years time on market and many success stories from customers encourage further development.

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