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Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information

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Abstract

Remote sensing from airborne and spaceborne platforms provides 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. The object-oriented approach 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 principal 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.

Keywords: 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 sensors 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 (Curlander and Kober, 1992; Haverkamp and Tsatsoulis, 1992; Tsatsoulis, 1993; Pierce et al., 1994; Serpico and Roli, 1995), e.g. for hyperspectral or high-resolution polarimetric SAR data (Curlander and Kober, 1992; Coulde and Pottier, 1996).

However, all these signal processing algorithms are applied on pixels or rectangular areas and do not take into account contextual information. Image processing methods, data and information fusion have to be added to exploit the full information, both of the physics of the sensor measurements and the context within the scene.

Additionally, results in signal processing are mostly presented in raster format which is not well-suited to fuse with results of digital photogrammetry and combination with vector GIS data.

Thus, there is a large gap between theoretically available information in remote sensing imagery and

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extracted and used information to support decision making processes.

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;
- fuzzy systems for improved and robust modeling of real-world dependencies and a detailed quality check of the resulting product;
- sensor and information fusion to use all available synergies.

In the following, we describe basic concepts of our approach, some parts of these explanations are taken from eCognition's UserGuide (UserGuide eCognition, 2003). We explain the concepts on some examples and discuss the enhanced possibilities due to the fuzzy classification.

2. Overview: from data analysis to image understanding using a hierarchical object network

The basic processing units of object-oriented image analysis are segments, so-called image objects, and not single pixels. Advantages of object-oriented analysis are meaningful statistic and texture calculation, an increased uncorrelated feature space using shape (e.g. length, number of edges, etc.) and topological features (neighbor, super-object, etc.), and the close relation between real-world objects and image objects. This relation improves the value of the final classification and cannot be fulfilled by common, pixel-based approaches.

Since at least two decades, processing power of affordable computers allows image processing and image segmentation. Therefore, these methods become applicable for operational remote sensing image analysis. First major advantages in this area were derived in studies for sea-ice analysis (Daida et al., 1990), object-oriented image matching (Heene and Gautama, 2000) and certain approaches for data compaction (Ghassemian and Landgrebe, 1988).

The first general object-oriented image analysis software on the market was eCognition (UserGuide eCognition, 2003). 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, which are independent of the particular methods. The network of these image objects is directly connected to the representation of image information by means of objects. Whereas the topological relation of single, adjacent pixels is given implicitly by the raster, the topology and interaction 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.

In many cases, a complete classification task consists of subtasks which have to operate on objects of different sizes. For example, to detect "single buildings" in "urban areas", analysis on different resolution levels, which are linked is necessary. This multi-scale analysis is possible with eCognition. The system allows representation of image information in different scales simultaneously by different object layers.

It is achieved by a hierarchical network 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, e.g. the numbers of single buildings in an urban area. Furthermore, the shape of super-objects can be changed based on sub-objects.

Image analysis 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 separation makes image analysis very flexible. Remote sensing experts develop sensor-specific methods to extract certain kinds of object primitives from sensor data, e.g. spectral characteristics for trees or 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 then does not need to have specific knowledge on the sensor characteristics.

That means after object primitives are identified, e.g. primitives which represent a part of a tree or a tree, the object and its neighbors, sub-and super-objects can be analyzed with a *forest* logic. Instead of processing all areas of an image with the same algorithm, differentiated procedures can be applied to different classified super-objects. The results will be much more appropriate. This is very similar to using different experts in manual image interpretation: The special knowledge of, e.g. urban planners or forest engineers is used for the dedicated analysis tasks for forestry and urban planning to get appropriate results. To enable this localized usage of expert algorithms is a specific strength of multi-scale object-oriented image analysis.

For successful information extraction, an iterative application of segmentation and classification is helpful.

Initial segmentation relies on low-level information, e.g. the pixel values and basic features of the intermediate image objects. The initial (multi-scale) segmentation provides image object primitives with a certain spectral behavior, shape and context. These object features enable a preliminary classification. After this step, the classification result can be used as high-level input for segmentation, a so-called classification-based segmentation. Typically, objects of interest are extracted by these iterative loops of classification and processing. Thereby, image objects as processing units can continuously change their shape, classification and mutual relations.

This circular processing results in a sequence of intermediate states, with an increasing differentiation of classification and an increasing abstraction of the original image information. In each step of abstraction, new information and new knowledge is generated and can be beneficially used for the next analysis step. 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 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 based on a hierarchical object network leads from mainly data-driven analysis to scene understanding.

3. Knowledge-based image interpretation

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

Main requirements of the information extraction process in a state-of-the-art image analysis system 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) consideration of the inherent uncertainties of the whole information extraction system, starting with the sensor, up to fuzzy concepts for the requested information.

Here, we focus on the object-oriented approach and fuzzy analysis of the object network to address items 2, 3 and 4.

3.1. 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 based on pixel resolution, the objects of interest often have their own inherent scale. Scale determines the occurrence or absence 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 area dimensions a pixel covers on the ground, scale describes the magnitude or the level of aggregation (and abstraction) on which a certain phenomenon can be described. Thus, studying an image in 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 which depicts an urban area, e.g. acquired by high-resolution satellite sensors, as Ikonos.

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

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

This example describes a 3-scale-level approach:

(1) trees, buildings and roads at a fine scale;
(2) groups of trees and groups of buildings aggregated to different settlement types at a medium scale;
(3) forest and urban area and open landscape at a coarse scale.

Between these scales there is a hierarchical dependency. One obtains settlement areas or even neighborhoods by aggregating houses, buildings, roads and other objects. 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 aggregation level. Both are of comparable scale and both are of high semantic abstraction.

These hierarchical scale dependencies are self-evident in each observation and description of real-world structures. However, 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. For each type, different characteristics are of interest. Thus, in order to analyze an image successfully it is necessary to represent its content at several scales simultaneously and to explore the hierarchical scale dependencies among the resulting objects.

It is obvious that this aggregation, which can be used for later abstraction, cannot be analyzed by just changing the resolution of the imagery. This would, moreover, lead to the loss of a lot of useful information.

3.2. *Image semantics—mutual relations between image objects*

One of the most important aspects of understanding imagery is information about image 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 of image regions. In human perception, processing of context information is in most cases consciously or subconsciously present and contributes essentially to the great capabilities of humans in image analysis.

In order to receive meaningful context information, image regions of the right scale must be brought into relation. This is an extension to the analysis of the image on different scales without semantic context as described in Section 2. For instance, the classification task to identify parks in very high-resolution imagery can be solved by the following approach: 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, 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 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, image objects have to be linked to allow low and high-level semantic and spatial context.

The image object network becomes a hierarchical image object network, when image objects of different scale at the same location are linked. Now, each object is characterized not only by its spectral, shape or texture features, but also by its unique neighbors, its sub- and super-objects.

Together with classification and mutual dependencies between objects and classes, such a network can be seen as a spatial semantic network.

3.3. Inherent uncertainties and vagueness

Various types of uncertainty influence information extraction from remote sensing data. Uncertainty starts with noisy sensor measurements with limited accuracy, degrading signal processing methods for data compression and filtering, ambiguous feature extraction and classification and ends with imprecise concepts of landcover and landuse classes.

3.3.1. Uncertainties of the sensor

Sensor measurements—the basic source for image pixels—have limited radiometric and geometric resolution. Limitations in radiometric resolution which are present even after careful calibration of the instrument reduce the distance of classes in the feature space. 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 landcover of the shore area. Thus, both geometric and radiometric resolution lead to reduced possibilities of unambiguous classification.

3.3.2. Uncertainties in image generation

The image generation process, e.g. for SAR images, 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.

3.3.3. Fuzzy concepts

Usually only fuzzy concepts exist for landcover and landuse. There is no exact threshold between densely and sparsely populated area, or between low and high vegetation. Therefore, whenever thresholds are defined they are mostly unsatisfactory idealizations of the real world and subsequently lead to problems during classification. If these thresholds are used for "ground truth" definition, classification results are compared with idealized reference data and thus performance estimation of the classification is not optimal.

3.3.4. Vague retrieval models

Information retrieval from remote sensing databases is based to a large extent on vague knowledge. The dependency between features and landcover or landuse is mostly only roughly modeled. Especially 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*.

3.3.5. Ambiguities due to limited feature space

In many cases the requested information for a specific classification task is not, or not unambiguously, contained in the available image data. This can be caused by spatial or radiometric resolution, by limited number of frequency bands or polarizations, or because the signal to noise ratio is too low. This reduced reliability of classification is important input especially for sensor fusion. The output of each sensor can be weighted by its suitability and reliability for a certain classification. This may also vary as reliability for optic analysis degrades for hazy or cloudy images.

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 inaccurate sensor measurements, vague class descriptions and imprecise modeling into the analysis approach. The degree of uncertainty for each object is part of the fuzzy classification result (Zadeh, 1965; Bezdek and Pal, 1992; Bandemer and Gottwald, 1995; Maselli et al., 1996; Benz, 1999). Taking these uncertainties into account within information extraction, the classification result is well suited as part of any decision support system.

4. Image objects and object features

The basic elements of an object-oriented approach are image objects. Image objects are contiguous regions in an image. We distinguish between image object primitives and objects of interest. Only objects of interest match real-world objects, 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 are attributed with 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 ratio of the mean values of two input channels A and B.

$$f_{r_{\mathrm{AB}}} = \frac{1/n \sum_n p_{\mathrm{A}(x_n)}}{1/n \sum_n p_{\mathrm{B}(x_n)}} \tag{1}$$

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 improves the reliability of statistic without smearing edges, since objects do not exceed edges. Of course homogeneous areas of mixed pixels can't be resolved. In ideal cases, this mixture would be detected since it is not matching the signatures of pure classes and therefore result in a reduced reliability of object classification.

Image object shape:

The closer object primitives are to objects of interest, the more image object shape features such as size, length or number of edges can be used as additional uncorrelated object features. Advanced shape features can be derived from object polygons and object skeletons. Since these features are independent of sensor characteristics they are robust versus sensor calibration and illumination conditions.

Image objects statistics, texture (e.g. Haralick measures; Haralick and Shapiro, 1992), and 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 neighboring objects can be evaluated, whereby the range 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.

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;
  b. line analysis based on sub-objects;
  c. class-related features: relationships to classified sub-objects, such as the relative area of 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 semantic features reduce ambiguities, allow landuse classification in addition to pure landcover classification and thus lead to a first step of scene understanding.

In the following, we describe the image object creation process.

4.1. Creation of image objects

Objects are created by image segmentation, which is the subdivision of an image into separate regions. Image segmentation is a long year research topic in the area of image analysis (Rosenfeld and Kak, 1976; Manjunath and Chellappa, 1991; Mao and Jain, 1992; Panjwani and Healey, 1995). This segmentation can be realized as an optimization process. Regions of minimum heterogeneity given certain constraints have to be found. Criteria for heterogeneity, definition of constraints and the strategy for sequence of aggregation determine the final segmentation result (see Fig. 1).

Fig. 1. Example segmentation result in eCognition.

Heterogeneity can refer to *primary object features*, such as standard deviation or gray tones, shape of the object, or texture on objects or on *higher order object features*, such as class assignment of objects. Segmentation methods using a 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. This advanced segmentation step creates objects, which are similar or close to the objects of interest.

Segmentation in eCognition (Baatz and Schäpe, 1999; Baatz and Mimler, 2002) allows both segmentation based on primary features (gray tone and shape) and—after an initial classification—the more advanced classification-based segmentation. The method is applicable for many data types with different dynamic and distribution. Constraints can be used to ensure exact reproducibility of segmentation.

As already mentioned in Section 3.1 image scale is very important for meaningful analysis. Therefore, eCognition provides segmentation on several scales. Scale selection is performed using certain parameters.

Details of eCognition's object creation approach are provided in the following sections.

4.1.1. 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 pair wise clustering process, the underlying optimization procedure minimizes the weighted heterogeneity $n\,h$ of resulting image objects, where n is the size of a segment and h a parameter of heterogeneity. In each step, that pair of adjacent image objects is merged which results in 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.

The procedure simulates the simultaneous growth of segments over a scene in each step to achieve adjacent image objects of similar size and thus of comparable scale. 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, such a sequence leads to slightly varying results dependent on the history of treated pixels and objects.

Constraints can be used to force an exactly reproducible segmentation on the same image. Here a global optimization criterion is used.

4.1.1.1. Definition of heterogeneity. Heterogeneity in eCognition considers as primary object features color and shape. The increase of heterogeneity f has to be less than a certain threshold.

$$f = w_{\text{color}} \cdot \Delta h_{\text{color}} + w_{\text{shape}} \cdot \Delta h_{\text{shape}}, w_{\text{color}} \in [0, 1,], w_{\text{shape}} \in [0, 1,] w_{\text{color}} + w_{\text{shape}} = 1 \quad (2)$$

The weight parameters (w_{color}, w_{shape}) allow adapting the heterogeneity definition to the application.

The spectral heterogeneity allows multi-variant segmentation by adding a weight w_c to the image channels c. Difference in spectral heterogeneity Δh_{color} is defined as following:

$$\Delta h_{\text{color}} = \sum_c w_c \left(n_{\text{merge}} . \sigma_{c,\text{merge}} - \left(n_{\text{obj\_1}} . \sigma_{c,\text{obj\_1}} + n_{\text{obj\_2}} . \sigma_{c,\text{obj\_2}} \right) \right) \quad (3)$$

with n_{merge} number of pixels within merged object, $n_{\text{obj\_1}}$ number of pixels in object 1, $n_{\text{obj\_2}}$ number of pixels in object 2, σ_c standard deviation within object of channel c. Subscripts merge refer to the merged object, object 1 and object 2 prior to merge, respectively.

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

$$\Delta h_{\text{shape}} = w_{\text{compt}} \cdot \Delta h_{\text{compt}} + w_{\text{smooth}} \cdot \Delta h_{\text{smooth}} \quad (4)$$

with

$$\Delta h_{\text{smooth}} = n_{\text{merge}} \cdot \frac{l_{\text{merge}}}{b_{\text{merge}}} - \left(n_{\text{obj\_1}} \cdot \frac{l_{\text{obj\_1}}}{b_{\text{obj\_1}}} + n_{\text{obj\_2}} \cdot \frac{l_{\text{obj\_2}}}{b_{\text{obj\_2}}} \right) \quad (5)$$

$$\Delta h_{\text{compt}} = n_{\text{merge}} \cdot \frac{l_{\text{merge}}}{\sqrt{n_{\text{merge}}}} - \left(n_{\text{obj\_1}} \cdot \frac{l_{\text{obj\_1}}}{\sqrt{n_{\text{obj\_1}}}} + n_{\text{obj\_2}} \cdot \frac{l_{\text{obj\_2}}}{\sqrt{n_{\text{obj\_2}}}} \right) \quad (6)$$

l is perimeter of object, b is perimeter of object's bounding box.

Thus, the *smoothness heterogeneity* equals the ratio of the de facto border length l and the 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_{compt} are parameters, which can be selected in order to get suitable segmentation results for a certain image data stack and a considered application.

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 exceeds a threshold t determined by the scale parameter, $t = \Psi$ (scale parameter), then no further fusion takes place and the 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 (Baatz and Schäpe, 1999).

4.1.1.2. 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 and a selection between alternative segmentation approaches is possible.

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.

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. This mode uses only compactness heterogeneity. The scale parameter 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 Fig. 2 the specific image object level can be sub-segmented. The results are compact sub-objects. 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, local curvature, etc.

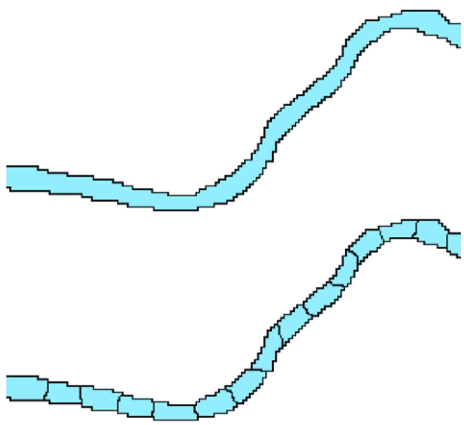


Fig. 2. Linear structure subsegmented into compact objects.

4.1.2. Validation of object creation process

Human interpretation and correction: In the usual image interpretation workflow automatic segmentation replaces 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 interpreters. Therefore, eCognition provides also the possibility of manual interaction (manual section and manual fusion).

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 polygon is covered by automatically achieved segments, best scores are given;
   - if the minimum number of segments are within the reference segment (lowest possible over segmentation),
   - if the minimum area of segments outside of reference polygon is covered.
b. The strength of segment borders is analyzed. The higher the increasing heterogeneity, if two segments would be merged, the less probable is their merging in the optimization process. Thus the segmentation result is less sensitive to parameter variations for segmentation for weights and scale parameter. The increasing heterogeneity can be interpreted as a border between the segments, which has to be overcome for merging. The higher this border for a certain segmentation parameter combination, the more stable is the result. The higher the ratio of the number of strong borders to the number of weak borders in a segmented image, the more stable and reproducible the segmentation will be for similar scenarios.
c. Combination of stable results according to validation in (b) and good results according to (a) provides a helpful assessment of segmentation quality.

4.2. Hierarchical object network

Objects created on different scales can be linked together to a hierarchical object network like the one displayed in Fig. 3. This has several advantages for image analysis.

4.2.1. Hierarchical network creation in eCognition

The levels of image objects are generated by the described multi-resolution segmentation described above.

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.

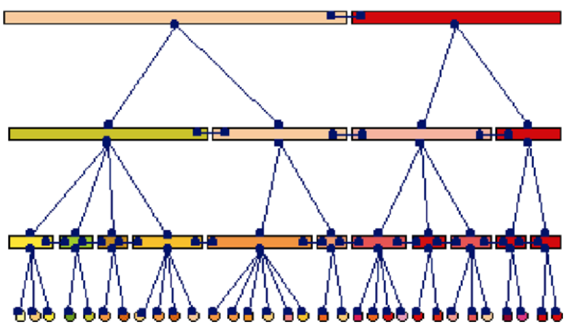


Fig. 3. Four-level hierarchical network of image objects in abstract illustration.

This network provides the base for successful information extraction: Relations between scales and combinations of scales can be used, e.g. one could focus based on the same image on trees, on groups of trees and on forest. Roads (extracted on fine scale) leading through forest areas (extracted on coarse scale) can be classified as *forest roads*. Based on the width of the roads a certain drivability can be assigned as feature in the output for a geo-information system. Furthermore, context information and semantics can be used to distinguish between trees within a forest or within an urban area.

4.3. 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. Within eCognition 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 the 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 or slightly abstracted polygons. 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 and is used for the computation of shape features. These polygons are referred to as shape polygons.

The computation of base polygons is done by means of a Douglas Peucker (Douglas and Peucker, 1973) algorithm.

The Douglas–Peucker algorithm produces in some cases relatively acute angles. In order to improve the result, angles smaller than 45° are detected. 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°.

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 exported. In order to avoid this effect, an additional, optional algorithm detects intersections and splits the affected vectors.

The *shape polygons* are created by means of a derivative of multi-resolution segmentation (Eq. (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 to the underlying base polygons. The resulting shape therefore, depends also on the threshold of the base polygons. A threshold larger than 0 will result in a stronger abstraction than the base polygons. Particularly, 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 orthogonal 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 threshold is reached.

4.3.1. Object features based on polygons

The shape polygons are independent of the topological structure as 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. These shape polygons allow computing additional object features, e.g. the number of straight edges, average length of edges and maximum length of edges. These features can be used to discriminate between manmade objects and natural objects: Artificial objects are usually characterized by few long straight edges, whereas natural objects are more irregularly shaped.

Skeletons are advanced object features based on polygons. For elongated objects they provide the centerline of and second and higher order branches. Thus, in addition to the road detected in remote sensing imagery the centerline of the street is extracted. This is of advantage for subsequent use of the information extraction result. The line can be exported to GIS and used for subsequent map production, where the road is not depicted as detected in the image but according to its importance and according to the map scale.

Skeletons are created based on a Delauney triangulation.

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 define a connection point, and
- end-triangles represent 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. An example is shown in Fig. 4.

Skeletons provide input for advanced automatic shape correction. For example high order branches of an irregular object can be cut automatically. A typical example is the separation of lower order streets from the main road for individual analysis. The automated object cut can be understood as pruning the object's skeleton from outside to inside.

4.3.2. Vector format import and export

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

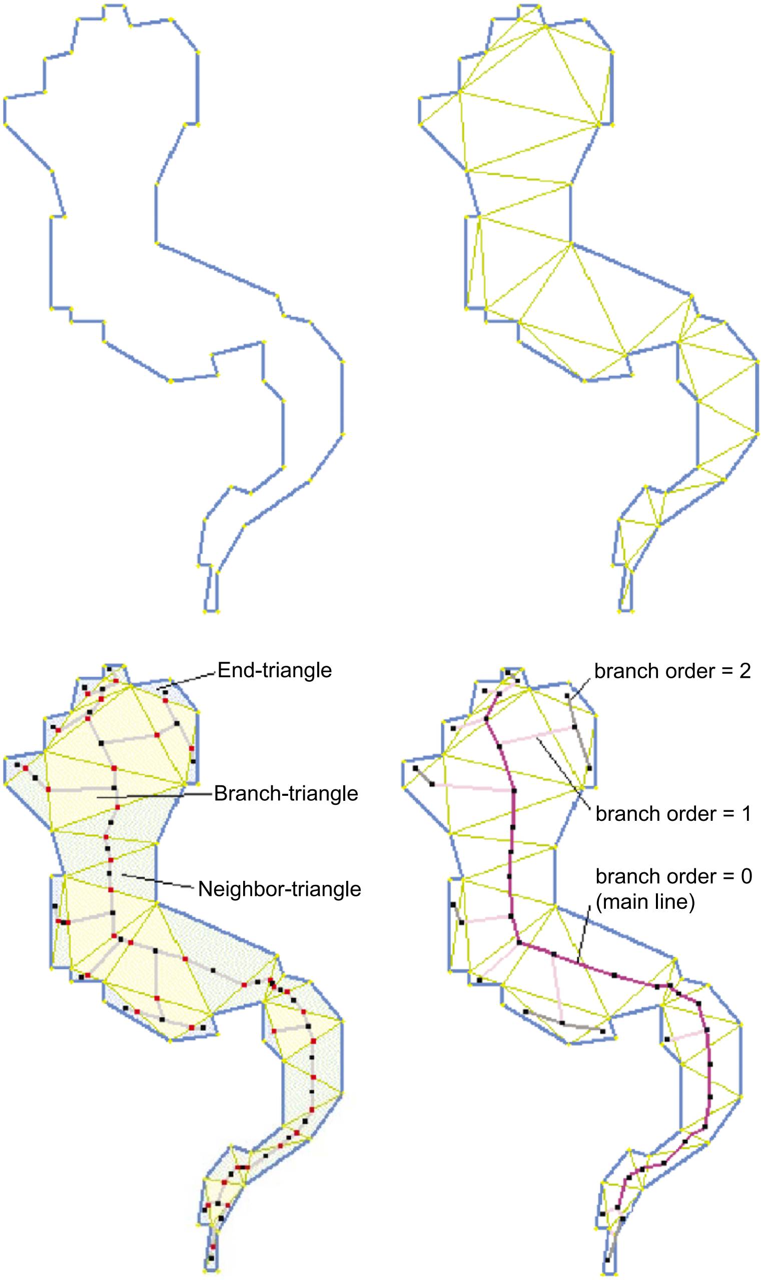


Fig. 4. Creation of skeletons based on a Delauney triangulation of image objects' shape polygons.

eCognition supports the import and export of thematic data in shape format. Since eCognition is a region-based analysis system, only polygons can be imported.

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.

5. Fuzzy classification

Fuzzy classification is beside neural networks (Gopal and Woodcock, 1996) and probabilistic approaches (Curlander and Kober, 1992) a very powerful soft classifier. As an expert system for classification (Tsatsoulis, 1993) 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 an n-dimensional tuple of membership degrees, which describes the degree of class assignment μ of the considered object obj to the n considered classes.

$$f_{\text{class,obj}} = [\mu_{\text{class\_1}}(\text{obj}), \mu_{\text{class\_2}}(\text{obj}), \ldots \mu_{\text{class\_}n}(\text{obj})] \quad (7)$$

Crisp classification would only give the information, which membership degree is the highest, whereas this tuple 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. Fuzzy logic can model imprecise human thinking and can represent 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, the combination of fuzzy sets, e.g. by fuzzy rule-base and defuzzification, which are briefly described in the following.

5.1. Fuzzification

Fuzzification describes the transition from a crisp system to a fuzzy system. It defines on an object feature certain fuzzy sets. These fuzzy sets represent object feature classes, e.g. "low", "medium" or "high".

These fuzzy object feature classes are defined by so-called membership functions. These functions assign a membership degree between 0 and 1 to each object feature value with respect to the considered object 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 Fig. 5, 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,

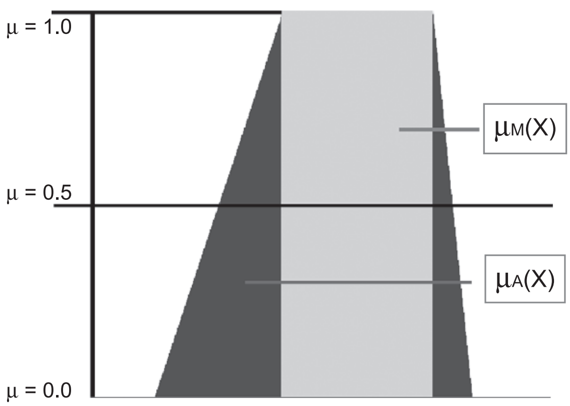


Fig. 5. Rectangular and trapezoidal membership functions on feature x to define a crisp set $M(X)$, $\mu_M(x) \in \{0,1\}$ and a fuzzy set $A(X)$, $\mu_A(x) \in \{0,1\}$ over the feature range X.

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 range of the originally crisp features. This simplifies working in a high-dimensional feature space with different feature value ranges and features of various types, e.g., backscatter from different sensors, geographic information, texture information and hierarchical relations.

For successful classification a deliberate choice and parameterization of the membership function is crucial. The function has to model the underlying relation between object features and classification as good as possible. The design is one of the most important steps to introduce expert knowledge into the system. Therefore, the better the knowledge about the real system is modeled by the membership functions, the better the final classification result (Civanlar and Trussel, 1986).

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 more vague the final classification.

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.

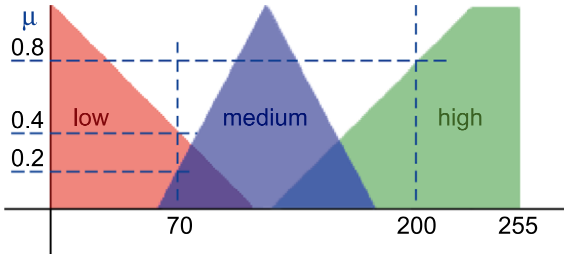


Fig. 6. Example for three fuzzy sets on feature x. The membership functions on feature x define the fuzzy set *low*, *medium* and *high* for this feature.

5.2. 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. An example is: "If" feature x is low, "then" the image object should be assigned to landcover 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 landcover W. According to the example in Fig. 6, in case feature value $x=70$, the membership to landcover W would be 0.4, in case $x=200$, the membership to landcover 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 independent 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 a tuple of return values for each of the considered output classes (see Fig. 7). These values represent the degree of class assignment.

It should be noted that, while fuzzy classification gives a possibility for an object to belong to a class, 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 provides one value for many objects. Whereas the probability of all possible events adds up to one, this is not necessarily true for possibilities. The not normalized possibility values provide additional information on the classification reliability for each object.

The higher the membership degree for the most possible class, the more reliable is the assignment.

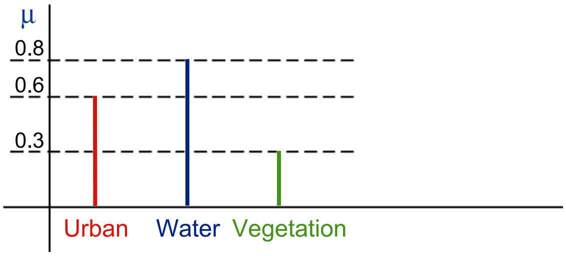


Fig. 7. Fuzzy classification for the considered landcover classes urban, water and vegetation. The image object is a member of all classes to various degrees; $\mu_{\mathrm{urban}}(\mathrm{obj}) = 0.6$, $\mu_{\mathrm{water}}(\mathrm{obj}) = 0.8$, $\mu_{\mathrm{vegetation}}(\mathrm{obj}) = 0.3$.

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

Equal membership degrees of an object to several classes indicate an unstable classification. Within the resolution cell and based on the provided class definition the classes cannot be distinguished. If the membership value is high and the system is well designed, this result indicates a class mixture within the resolution cell. If the membership value is low, the assignment is unreliable and the object will be flagged for quality assurance in subsequent processing steps. A threshold for the required membership degree is

Fig. 8. Image mosaic provided by the forest mapping management, Austria.

Fig. 9. Provided polygons of buildings.

defined. If this threshold is not reached, the object remains "unclassified".

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 best 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.

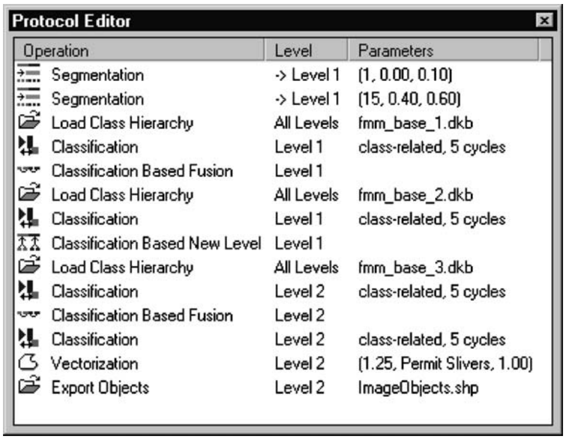
5.3. Defuzzification

To produce results like maps for standard land-cover and landuse applications, the fuzzy results have to be translated back to a crisp value. To this end, the maximum membership degree of the fuzzy classification is used as crisp class assignment. This process is a typical approach for defuzzification of fuzzy classification results.

If the maximum membership degree of a class is below a threshold, no classification is performed to ensure minimum reliability.

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

Fig. 10. Hierarchical rule-base structure in eCognition.


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

Fig. 11. Protocol for automatic analysis of mosaic.

As this output removes the rich measures of uncertainty of the fuzzy classification, this step should be only performed if necessary and as late as possible in the whole information extraction process.

Further information on fuzzy systems in image analysis and remote sensing can be found in Bezdek and Pal (1992), Maselli et al. (1996), Benz (1999) and Jaeger and Benz (2000).

6. 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 (0.5 m) RGB aerial orthoimages of FMM (Forest Mapping Management), an Austrian. Input files were the image mosaic (Fig. 8) and shape files, showing building footprints (Fig. 9). This information was to be updated and extended by polygons for impervious areas.

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

The classification is applied on two levels (Fig. 10). The hierarchical rule-base defines on level 1 first the classes "roof" and "non-roof". "Non-roof" is further subdivided into "non-impervious", "shadow", "impervious" and "probably impervious". "Probably impervious" is split in "could be impervious" and "not likely to be impervious". "Shadow" is classified as "shadow over vegetation", or "shadow over impervious area".

This hierarchy in the 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 fuzzy 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 objects like buildings cast shadows.

The classification strategy for this application consists of iterative segmentation and classification. The steps, parameters and rule-bases are stored in a

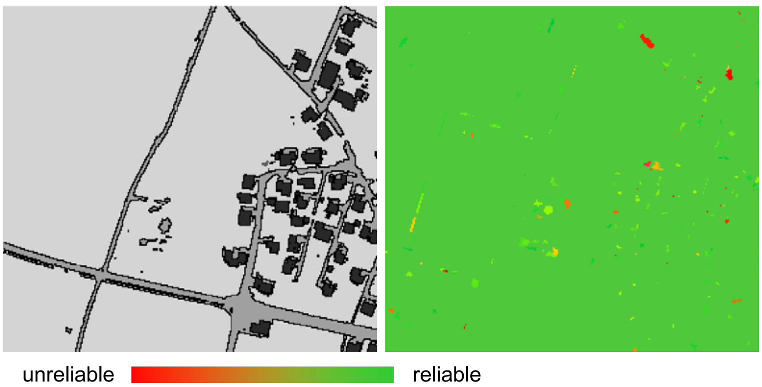


Fig. 12. Classification map (left) of buildings, other impervious areas and non-impervious areas. Reliability map (right), where medium grey areas mark objects with highly reliable classification, while the rest shows unreliable classification.

id	Best Class ID	Best Membership	Mean
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		Buildings	Non impervious	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

Fig. 13. Example of statistics for export.

protocol. This protocol can be used for batch processing to apply the information extraction on the whole image mosaic.

Fig. 11 shows the steps and parameters of analysis for this example. First, a segmentation is performed with different parameter settings to get the two levels of object primitives. A first class hierarchy (fmm_base_1.dkb) is loaded and used in the next step for classification. Based on this preliminary classification, first objects of interest are created from object primitives, by classification-based fusion. Similar steps are performed until the final classification is applied on level 2. Objects of level 2 are vectorized and exported to a shape file.

Fig. 14. Updated and extended shape file.

Results are:

- a classification map and a reliability map (Fig. 12),
- statistics with relation to certain classes and with respect to single objects (Fig. 13), and
- an updated and extended shape file (Fig. 14).

The reliability map (Fig. 12, right) is important for manual post-processing. Only those objects flagged as having a low reliability have to be manually assigned after inspection of the aerial images or, if no decision is possible based on the image, in-situ observations.

Thus, the method does not replace all manual interactions, but reduces the amount significantly. 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.

The first table in Fig. 13 shows a unique ID for each object. The crisp classification is provided by the "best class" column, in which the class is coded by a number. Any object feature can be exported along with the object, here the membership degree of the best class and the mean value is added as an additional column.

The second table in Fig. 13 shows information on all objects of a certain subset, e.g. the number of objects assigned as buildings equals 218, the total area of impervious object is 121 684 m^2, the mean area of impervious objects is 137 m^2, the maximum area of one impervious object is 54 654.8 m^2, etc.

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 an aerial image mosaic and update of GIS-information.

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

7. Conclusion

The main focus at Definiens is to produce software for the analysis of complex systems. This can only be done, if the high degree of mutual relationships and actions at different scales such as context information, semantic and hierarchical structure are taken into account. With Definiens' Cognition Network Technology, the basis is available to analyze not only images but also texts from many different domains, and to combine the information from heterogeneous sources to support decision makers.

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