OBJECT-BASED IMAGE ANALYSIS IN REMOTE SENSING APPLICATIONS USING VARIOUS SEGMENTATION TECHNIQUES

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Abstract. Extensive education, research and development activity is carried out in geoinformatics at Eötvös Loránd University (ELTE), Faculty of Informatics, in cooperation with the Institute of Geodesy, Cartography and Remote Sensing (FÖMI). It includes the teaching of subject "Remote Sensing Image Analysis", research of segment-based classification of remote sensing images and its applications in operational projects.

Investigation of segmentation methods is embedded into the classification problem. *Segments* are homogeneous areas of images, consisting of neighboring pixels. Segment membership of pixels conveys valuable geometric information to classification step. This article gives a summary on several merge-based and cut-based segmentation methods.

The application of segmentation is not only an option, but a necessity in the processing of very high resolution images, as their pixels usually cannot be interpreted individually. Segments are assigned with several attributes (e.g. texture) derived from geometrical properties. This leads to the advanced approach called *Object-based Image Analysis* (*OBIA*).

As an application, the task of delimiting tree groups and scattered trees in pastures will be presented in detail. Three further applications will also be shortly introduced.

Key words and phrases: Remote sensing, object-based image analysis, segmentation, education.

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1. Introduction

Extensive education, research and development activity is carried out in geoinformatics at Eötvös Loránd University (ELTE), Faculty of Informatics, in cooperation with the Institute of Geodesy, Cartography and Remote Sensing (FÖMI). Results gained from this collaboration were comprehensively presented in [7]. It includes the teaching of the course "Remote Sensing Image Analysis" in the Geoinformatics educational module, research of segment-based classification of remote sensing images and its applications in operational projects.

Basic research of segmentation methods is embedded into the classification problem. The difference between pixel-based and segment-based classification methods is obvious in the determination of land cover categories. *Segments* are homogeneous areas of images, consisting of neighboring pixels. Segment membership of pixels conveys valuable geometric information, which can be utilized in ambiguous cases of classification. Results achieved with segmentation methods have been presented in [11], [13] and [10]. The newest article is [4], which gives a summary on several merge-based (bottom-up) and cut-based (top-down) segmentation methods investigated by the authors.

Very high resolution satellite images and ortho-photos gain increasing importance in current operational applications. Individual pixels of these images usually cannot be interpreted in themselves. Therefore, the application of segmentation is not only an option, but a necessity in the solution. Recently a new paradigm, called *Object-based Image Analysis* (*OBIA*), has emerged (see e.g. [8] and [2]). Its aim is to partition remote sensing images into meaningful objects, and assessing their spatial, spectral and temporal characteristics. Its basic step is segmentation. It includes the attribution of segments, that is, the assignment attributes that usually express geographic information, e.g. textural, shape and neighborhood properties. A higher level objective of OBIA is the replication of human interpretation. This way work processes may be automatized, and with the reduction of subjectivity, results become more repeatable. OBIA suits the trend of object-oriented approach in software technology.

The task of delimiting tree groups and scattered trees in pastures will be presented in depth, which is used in relation with agricultural subsidies. Three further applications will be shortly introduced: the surveying of red mud spill, the recognition of ragweed and the recognition of built infrastructure in rural areas. These applications are tightly connected to projects of FÖMI. In the operational processing chain, either pixel-based classification or visual interpretation is used to recognize and delineate land cover categories. In our research, the target is to provide a useful solution using object-based image analysis. These results have been partially presented in [12].

2. Segment-based classification

In the *thematic classification of remote sensing images* it is always a key question to find the link between the objects of "real world" and those of images (see [14]). To achieve proper detection of features in mapping, image objects that fit land cover objects need to be delineated and they must be classified into predefined classes. Since the birth of remote sensing, the rich spectral content of satellite images has been showing its strength in the differentiation of land cover classes. But it is not always enough to utilize only spectral information. Traditional pixel-based classification methods completely disregard spatial relations. To overcome this drawback, *segmentation* was introduced with the aim of extracting neighborhood information and preserving natural homogeneity. Segment is a contiguous set of spectrally similar pixels. Segments form a complete disjoint coverage of an image. Segmentation methods are usually iterative, and segments in different iteration steps can be organized into a hierarchical system.

Within the wide range of segmentation methods, authors primarily deal with region-based algorithms. During the last years, gradually a fully segment-based classification framework has been designed and implemented. First, the Sequential linking method (see below) has been improved ([11]). Afterwards, a special variant of pixel-based classification has been used for the segments obtained in previous step ([13]). Finally, a real segment-based clustering and classification procedure has been implemented ([10]). This is a modular framework, that is, all the components – segmentation, clustering, classification – can be changed. The following segmentation methods were implemented and analyzed.

- *Merge-based, "bottom-up" methods* start from pixels: in the beginning, every pixel of the image forms an individual segment. During the iterations of algorithm, segments are gradually merged.
  - *Sequential linking* ([9]) deals with the statistical homogeneity of segments. In a preparatory step, small groups of pixels (for example, 2 by 2 squares) are joined into cells. Iteration consists of row-wise traversing through cells, attempting to join the current cell to a segment. Because of sequential traversing, time requirement is a linear function of image size. It is, however, a serious drawback of the original algorithm that the resulting segments are strongly influenced by traverse order. Some improvement has been made in the above-mentioned framework.
  - *Best merge* algorithm ([1], [17] and [15]) overcomes the above mentioned strict traverse order: it chooses any two neighboring segments over the image if their contraction is optimal with respect to certain criteria. Best merge is a greedy algorithm. In the variant

implemented by the authors of this article, image is represented by a graph. The efficiency of implementation is assured by advanced disjoint-set data structures.

  – The idea of *graph-based merge* ([5]) comes from graph theory. Segments are characterized by their heterogeneity, which is formally defined using graph notation. In each iterative step, adjacent segments are merged. Edges are taken in the descending order of their weight, and it is decided whether the two segments belonging to the two end nodes can be contracted. The decision is based on the internal variability of segments. An efficient implementation is based on union-find data structure.

- *Cut-based, "top-down" methods* behave the opposite way. In the beginning, the whole image is considered as one large segment. In each iteration step, an appropriately chosen segment is cut into two smaller ones. All the cut-based methods the authors dealt with are developed and implemented on the basis of graph representation.

  – In the *Minimum mean cut* algorithm ([18]), the edge weights are proportional to the spectral difference between segments that are represented by the respective subgraph.

  – *Minimum ratio cut* algorithm ([19]) is an improved and generalized variant of minimum mean cut. Two weight functions are used, and criteria are defined with their ratio.

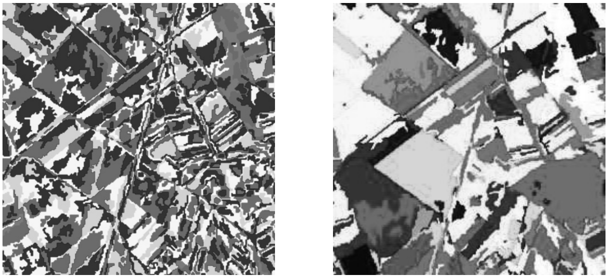
  – *Normalized cut* algorithm ([16]) is also derived from minimum mean cut, using the same weight function.

In general, images and segmentation algorithms can be represented by undirected graphs. Vertices correspond to pixels. Edges connect vertices of neighboring pixels. Weights of edges are assigned according to the relation between pixels they are connecting. Within the graph, segments can be described by subgraphs. Graph representation of cut-based algorithms subdivides edge set into disjoint subsets. This way only those edges remain in the graph that connect pixels within segments. Our implementation of graph-based algorithms presented above is strongly supported by efficient data structures and algorithms, which resulted in the asymptotic decrease of running time. In a part of cases, this improvement has been theoretically justified as well ([4]).

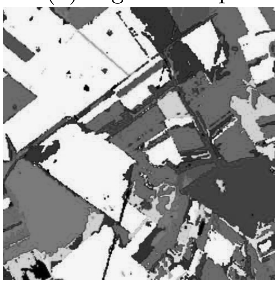
The result of segmentation is a thematic image, called segment map, containing the numbers of segment the pixel belongs to. As a result of earlier research and development, a fully segment-based classification method has been developed. The steps of pixel-based classification have been adapted to segments. Segmentation is followed by *clustering*, and then the final *classification* is carried out.

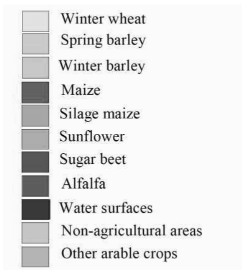
(a) May 06, 2003 (b) June 30, 2003 (c) August 11, 2003

A time series used for development and testing



(d) Segment map (e) Cluster map





(f) Classification (g) Legend of thematic classes

The steps of the segment-based classification

Figure 1. The illustration of Best-merge method

An illustration of Best-merge method can be seen in Figure 1. The upper row shows a time series chosen from several sample areas used for development and testing. The rest of the figure shows the result of three steps of classification process. The colors seen in the thematic images showing different phases are independent of each other. The illustration of segment map (1.d) is a six-colored image, where neighboring segments are distinguished by different colors.

During clustering, segments are merged into clusters; segments belonging to the same cluster may appear at different places of the image, depending on their statistical properties. Clusters in (1.e) have randomly chosen unique colors. In the image showing classification result (1.f), thematic classes appear according to a pre-defined legend (yellow = winter wheat, red = corn etc.; see Figure 1.g).

With the introduction of fully segment-based classification, the thematic accuracy grew to 91-95%, about 2-3% more than that of pixel-based method. Procedures are sensitive to parameters, but they less depend on the segmentation algorithm chosen. Run-time has dramatically decreased, as the number of objects to be dealt with is less by magnitudes.

3. Object-based image analysis: a case study

A fundamental shift of paradigm took place during the previous years with respect to the earlier research and development work.

- A professional image processing software package, named *eCognition* (formerly: *Definiens*) has been introduced, which is devoted to object-based image analysis.
- Beside the independent implementation of algorithms, the segmentation methods built into eCognition are used.
- The advanced attribution capabilities of eCognition is highly utilized.
- Very high resolution images (with pixel size less than or equal to 1 m) gain increasing significance. Pixels are usually much smaller than image objects, therefore the interpretation of individual pixels is often not possible. Segmentation cannot be ignored.
- As a consequence, OBIA has become the adequate tool of solution in many current tasks.

In Sections 3 and 4, four applications are shown where the task is solved by *object-based image processing,* using the eCognition software suite. The applications are linked to running projects of FÖMI. Research results achieved so far regarding the first three applications have been published in the master thesis ([6]), and in [12]. First application will be described in more details in this section.

3.1. Identification of ineligible land

One of the largest tasks of FÖMI is the operation and *updating of the Land Parcel Identification System (LPIS).* In Hungary, this is the exclusive reference system of area-based EU subsidies since 2004, in which all the agricultural parcels can be identified. As cultivation structure continuously changes, LPIS must be regularly updated to reflect current status. The basis of updating is the ortho-photo coverage, which is renewed in every year for about one fourth or one third of the country.

The basic areal unit is called physical block, which is bounded by borders stable in time. Beside block boundaries, LPIS contains many geoinformatic coverages, called *thematic layers* (e.g., Less Favored Areas, Nitrate Sensitive Areas, layers related to Agri-Environmental Measures). In LPIS, an important property of areas is whether they are *subsidized (eligible for agricultural payments).* The delineation of eligible and ineligible areas within physical blocks is also stored as a thematic layer.

The goal of application is *to automatically delineate (ineligible) scattered trees and bushes* appearing on (otherwise eligible) pastures. This task cannot be correctly solved with pixel-based classification, as the land cover units (trees, bushes, spots of pasture) are significantly larger than pixels. Furthermore, the differentiation cannot be made based solely on the intensity values of pixels; neighborhood information must be taken into account as well. The half meter spatial resolution of ortho-photos provides great geometrical accuracy. However, local spectral properties make classification harder, as it is difficult to distinguish between objects belonging to tree groups and similar segments actually belonging to other types of land cover. In some cases, the question cannot be decided even by visual interpretation. Continuous effort is made to automatize the task of delineation. Segment-based classification was proven to be appropriate in the majority of cases examined.

3.2. The software environment

To solve the delineation task, the eCognition software suite is applied. It contains several built-in proprietary segmentation procedures, which are not exactly the same that were presented in the last section. But the theoretical knowledge of segmentation and the experience gained with their implementation greatly helps in the proper use of this software suite.

Input consists of raster images. For the delineation of scattered trees, color infrared (CIR) ortho-photos with sub-meter resolution are applied. Besides, very high resolution (VHR) satellite images can also be used. The main output is a thematic vector (shapefile) with the classification results, which can be used in other GIS programs.

The software eCognition deals with a hierarchical system of images and image objects. Segmentation and classification steps are executed to derive objects from the level of pixels. Depending on the complexity of task, it may consist of several steps. The eCognition suite provides plenty of procedures built from elementary algorithms. Their choice and parameterization requires the theoretical knowledge of segmentation and photogrammetry. Publicly known and proprietary segmentation algorithms have been implemented under the names Chessboard, Quadtree, Contrast Split, Spectral Difference and Multiresolution etc. Classification takes segments as input. A plentiful system of sophisticated criteria is used for classification. Beyond usual statistical measures, geometrical and textural features, membership functions in class hierarchy and statistical distributions are available. Commands and functions are organized into Rule Sets.

When processing large images, eCognition is able to apply the "divide and conquer" approach: the image is split into smaller, equal-sized tiles, which may be processed in parallel; finally, the results of tiles are "stitched" together.

3.3. Segmentation

It is a basic requirement that segment map shall follow the boundaries of objects by preserving inhomogeneities and by keeping together neighboring homogeneous areas. Red and near-infrared bands and NDVI index (Normalized Difference Vegetation Index) are taken into account in homogeneity criteria.

In our case, segmentation consists of several steps. The first one divides the image into homogeneous initial objects, which are contracted into larger objects in the second and third steps. If necessary, some segments are cut into smaller ones in the fourth step. Segmentation algorithms presented below are flexible in the sense that they can handle different levels of processing.

- When running an algorithm for an unsegmented image, they behave as described in Section 2.
- When running a merge-based, "bottom-up" algorithm on a previously segmented image, the basis of contraction is the set of existing segments instead of individual pixels. That is, pixels belonging to the same segment remain together, and ones belonging to different segments may be contracted into the same segment.
- When running a cut-based, "top-down" algorithm on a previously segmented image, the basis of splitting is the set of existing segments instead of the whole image. Pixels belonging to the same segment may be separated into different segments.

The following segmentation algorithms were applied during the delimitation of pastures with trees.

1. Quadtree-based segmentation
   Image is subdivided into a quadtree grid with this "top-down" method.

Square-shaped objects are obtained (with side length of power of two). The maximum difference between pixels within one object is determined by the *scale* parameter. Using the results of this step as initial objects, computational load is largely reduced in the subsequent steps.

2. Multiresolution segmentation
   This is a "bottom-up" segmentation method based on pairwise region merging technique (see [20]). It contracts two objects, A and B if and only if B fits the best to A (among the neighbors of A) and A fits the best to B (among the neighbors of B), that is, they mutually fit the best to each other.

   During the execution of this algorithm, initial objects are contracted into larger objects until they reach a given homogeneity threshold, which is derived from the spectral and shape homogeneity value. In each iteration those objects are contracted that mutually fit the best to each other. The algorithm is finished when no other contractions may take place.

   Maximum heterogeneity value of an object is defined as the linear combination of a spectral (color) and a shape heterogeneity value. In color value the different spectral bands may be taken into account with different weights. Shape value incorporates a compactness parameter.

   Using human expertise, appropriate values have been found for the above mentioned parameters. In the theoretical research presented in [10] it was aimed to find the optimum parameter values by using formal accuracy assessment. However, this was not the goal in this case study.

3. Spectral difference segmentation
   The result obtained in the previous step correctly follows the differences and the borders of ground objects. However, it tends to create spectrally similar, small neighboring segments, which should be contracted. This contraction is accomplished by the Spectral difference segmentation, which is therefore again a "bottom-up" method, and is generally designed to refine raw segmentation results. The algorithm contracts two neighboring objects if and only if the difference between their average intensity is smaller than a pre-defined parameter. The spectral bands that are taken into account in the calculation can also be chosen.

4. Contrast split segmentation
   In some cases, the previous steps yield objects that can be clearly partitioned into lighter and darker areas. It is worth subdividing these objects, thus reducing the number of possible target categories. This "top-down" algorithm searches for the optimal intensity threshold in every object which maximizes the contrast between light and dark parts.

Evaluations carried out on several test areas have proven that the segment map obtained in these steps is appropriate for further examinations.

3.4. Classification

It is difficult to define the properties of target categories, that is, vegetation with trees in our case. Spectral properties are significantly influenced by tree species, vegetation density and illumination. However, we can address these difficulties with the possibilities of OBIA.

First of all, we assume that the geometric and texture properties of vegetation to be detected (trees and bushes) are different from the other kinds of vegetation (primarily arable land, grassland and other natural land cover types). This assumption is justified by preliminary visual examination. The texture of foliage of trees is less homogeneous and less structured than that of other vegetation. Besides, one can formulate other geometrical criteria, primarily concerning the size of objects.

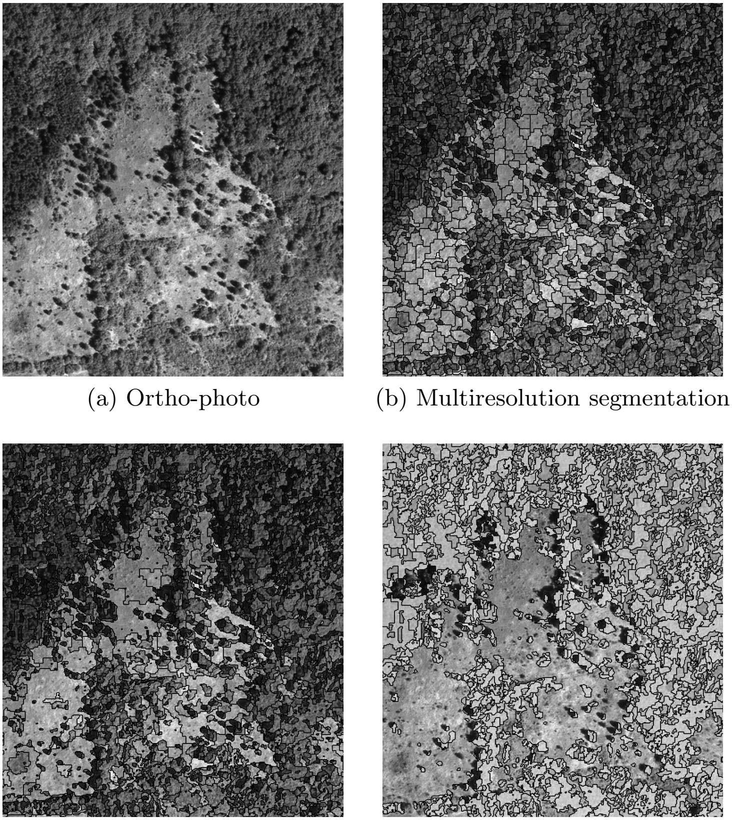
Texture is measured in two ways in this application. Inhomogeneity is simply characterized by the spectral deviation of segment. Besides, several GLCM-based measures (homogeneity, entropy) are examined. GLCM (Grey Level Co-occurrence Matrix) is a square matrix. Its height and width is equal to the number of grey levels in the spectral band to be characterized (radiometric resolution). In the simplest case, a P_{ij} element of the GLCM matrix P is the number of neighboring pixel pairs in the image having value of i and j, respectively. Instead of direct neighbors, pixels situated at a given distance can also be used. After counting pixel pairs, the GLCM matrix is made symmetric by adding its transposed matrix to it, and finally it is normalized by the number of elements. This way the elements of GLCM constitute an empirical probability distribution.

Texture is characterized by the statistics derived from GLCM. *Entropy* measures the disorder, or in other words, unpredictability or randomness of texture. Considering the elements of GLCM as probabilities, entropy is calculated in the same way as in information theory. *Homogeneity* measures the closeness of elements in the GLCM to the GLCM diagonal. Its value is high if the non-zero elements of the matrix are situated in the proximity of the diagonal.

It has to be noted that this approach is not free of errors. For example, the encroachment of weeds in homogeneous vegetation or the movement of agricultural machinery may cause inhomogeneity that can lead to erroneous classification (second-order error). Furthermore, unusual homogeneity may appear in the foliage of trees, also leading to misclassification (first-order error). These cases of erroneous classification can be partially filtered out using geometric constraints. Difficulties arise mainly at the border between areas of different land covers. As the goal of application is the correct indication of these borders, the full automatization of the delineation process cannot be allowed.

It is not the aim to make distinction between tree species. The definition of target categories is based on spectral properties extracted from samples of different areas with trees, independently of species. Classification is based on maximum-likelihood decision. Results can be improved using geometric properties. A part of them is defined by the parameters of application (minimum area to be delimited, the handling of surrounded areas). The other parts are related to image properties (surrounded shadows in foliage, local inhomogeneities within contiguous areas).

Some steps of the classification process on a sample area is shown in Figure 2. In the picture showing final classification results (2. d.), yellow color indicates segments classified as trees based on spectral and textural information, while in the case of segments marked in cyan, only geometrical properties were taken into account.



(a) Ortho-photo

(b) Multiresolution segmentation

(c) Contrast Split segmentation

(d) Classification

Figure 2. The steps of delineation of tree groups

4. Other applications

In last section, the OBIA solution of delineating ineligible areas on eligible pastures has been examined in details. This section gives an overview of three other projects. In these projects, similar development environment and processing methods were used, with slight modifications.

4.1. Observation of red mud spill

An important task of remote sensing is *the surveying of environmental and industrial disasters.* The second application is the detection and documentation of area affected by red sludge (red mud). On 4 October 2010, *industrial red sludge spill caused serious environmental damage* in the surrounding of Ajka town (North-Western Hungary). It was important to urgently deliver map information of spilt areas to help the assessment of damage and salvage. Five-band RapidEye images (with spatial resolution of 5 meters) and eight-band WorldView-2 images (2 meters) were used to monitor red mud spill. These images provided the possibility to exploit several different spectral features. Geometric and texture features were also very important in the differentiation between inundated and clear areas, this is why object-based image analysis has been chosen for the processing.

Segmentation was divided into the following three steps.

1. The first one created the initial image objects; its result was a good approximation of the expected segment map. This was a *multiresolution segmentation* algorithm using two NDVI-like indices (the first one was calculated from red and green, the other from red-edge and red bands). In this state the segment map may contain some local errors caused by inhomogeneities, therefore we had to use fine-tuning segmentation steps.

2. In the second step a *contrast split segmentation* was applied to divide false objects using the green spectral band. Local errors were corrected in this step, but some small objects were created in homogeneous areas as well.

3. Finally a *multiresolution segmentation* using the red spectral band took place in order to filter the unwanted small objects created in the second step. Final objects delineated in this step correctly follow the boundaries of spill. Figure 3 (a) shows a zoomed part of the final result of segmentation.

Classification was performed with sample selection and Maximum Likelihood method. The final goal is to delineate inundated area. In the intermediate steps of processing three classes were defined: open sludge surface, inundated soil and inundated vegetation. As the availability of on-the-spot reference data was limited, the training of classification was based on the difference seen in the images. These three classes are statistically described with the combination of some (few) sub-classes, which are not completely disjoint, but their overlap is minimal. Original band values, vegetation indices and their standard deviation were used in the classification, taking into account red, red-edge and near infrared bands.

Geometric properties have also been used in the classification process. The spectral and textural features of bare soils are very similar to those of spilled, but not fully flooded areas. They were separated by a simple smoothing, using the categories of neighboring objects. In Figure 3 (b) the whole processed area can be seen, with a box showing the location of zoomed part seen in 3 (a).

RapidEye image was processed with a similar, but somewhat simpler method than the one used in the case of WorldView-2. The spectral bands used in the processing of WorldView-2 image are available in RapidEye as well, but the variations stemming from different spatial resolution have to be taken into account.

(a) Segmentation (b) Classification

Figure 3. Segmentation and classification result of WorldView-2 image

4.2. Ragweed monitoring

Among invasive alien species, *ragweed* causes serious problems in Hungary, because of the *allergenic effect of its pollen.* Since 2005, remote sensing highly supports its exemption (see [3]). The majority of *pollen strain comes from large ragweed spots situated in agricultural areas.* Remote sensing exploration is targeted at finding spots with size of 1 ha or larger.

Ragweed recognition differs from "traditional" arable land mapping tasks in the sense that both spatial and temporal behavior of ragweed is very irregular. The basis of recognition is the identification of differences from arable land crops and the textural changes caused by the appearance of ragweed. Ground reference data collected in the field near to the date of satellite images were necessary to the derivation of training and test areas.

Traditionally, remote sensing detection of ragweed is carried out by the pixel-based processing of high resolution (HR) satellite image time series. As an experimental research project, very high resolution satellite images were processed with a segment-based method. It was not an aim to improve the result of pixel-based procedure.

Segmentation and classification is carried out in several turns, targeting different crops or land cover categories (cereal stubble, sunflower, soybean) in each turn. Within the examination of a crop category, the aim is to detect inhomogeneities caused by the presence of ragweed in agricultural parcels. This is why it is important to preserve local features, textures and inhomogeneities. Running one segmentation method has been proven to be sufficient to reach the expected result. A *multiresolution segmentation* with strong shape criteria was applied in green, red, red-edge and near-infrared bands. Using shape criteria prevents creating objects that intersect with several crop categories.

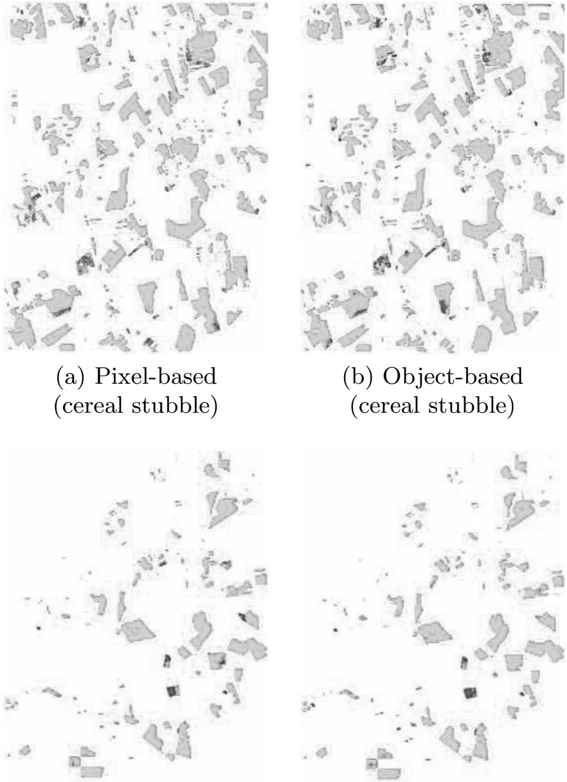
In the accuracy assessment of segment-based processing, the result of traditional processing chain was considered as reference. The matching between results of segment-based and pixel-based processing is about 90%, which is illustrated in Figure 4.

4.3. The recognition of built infrastructure in rural areas

Beside agricultural and disaster monitoring tasks, *the surveying of rural or built environment* is also an important application of remote sensing. Different kinds of monitoring tasks – for example, the examination of expansion and *re-structuring of cities,* ground tasks and aboveground mining – can be accomplished by using remote sensing data of appropriate resolution.

In this subsection the object-based analysis of ortho-photos in rural monitoring will be introduced. In order to achieve accurate evaluation results at the spatial resolution of ortho-photos (0.5 m pixels), auxiliary information is needed to complement spectral information; for example, LIDAR measurements must be used.

Using OBIA methods, it is vital to carry out appropriate segmentation. In rural environment, spectral information is not always enough for the proper classification of some kinds of objects. For example, roads, concrete surfaces and buildings with grey roof are difficult to distinguish. In the case of vegetation, classification is supported by several indices like NDVI, but there is no



(a) Pixel-based (cereal stubble)
(b) Object-based (cereal stubble)
(c) Pixel-based (soybean)
(d) Object-based (soybean)

Figure 4. The matching between results of segment-based and pixel-based processing (red indicates ragweed infection)

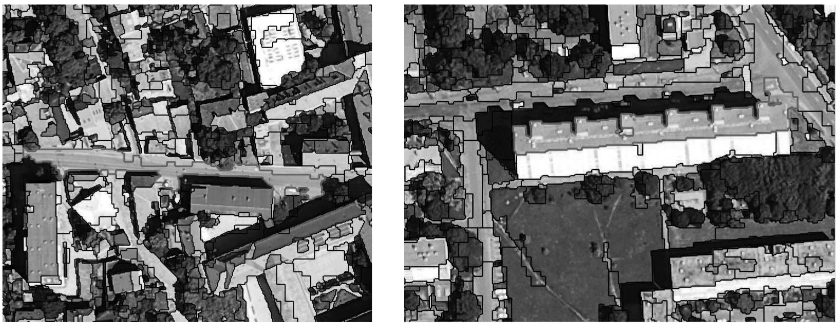
such tool in the classification of infrastructure. On the other hand, geometry provides useful help in OBIA. It is a basic requirement that segment map shall preserve geometric properties, spatial relations of "real world" objects.

As in the case of the processing of pasture with trees (presented in 3.1), a segment map is derived in four steps. Quadtree-based and multiresolution segmentation is followed by two runs of spectral difference segmentation, using different parameters. As the result, initial objects are formed.

In the classification step, the principle is the tracking of geometric properties of surface objects. Compound geometric measures are primarily used in the recognition of road and railroad networks. While the radiometric properties of roads and roofs are rather similar, the geometric measure *density* effectively makes a distinction between them. The density measure of the segment emphasized with red in Figure 5 (a) is significantly greater than that of other, spectrally similar segments; this makes it unambiguous that this segment belongs to a road.

Density describes the distribution of the pixels of a segment in space. It is calculated by the number of pixels forming the image object divided by its approximated radius. According to this calculation, the most "dense" shape is a square, while elongated segments have lower density ([20]).

The usage of this measure is made difficult by shadows, vehicles and even road markings, as they occasionally separate segments. Another difficulty is that buildings in a row may behave geometrically like roads. This is illustrated in Figure 5 (b), where the roof of the apartment building (with low density) has been contracted into one segment with a part of the neighboring road. These difficulties may be overcome by the usage of accurate height data (for example, LIDAR or stereo evaluation).



(a) A part of a road (b) A special kind of roof

Figure 5. Segmentation of rural environment

5. Summary

This article has presented some results of *scientific work* at ELTE Faculty of Informatics, which was supported by *institutional cooperation* with FÖMI. Beside education, the research and application of segment-based classification and object-based image analysis are the central fields of common work.

During the last years *several segmentation methods have been implemented,* tested and improved. Some of these methods have been applied in the *segment-based classification of remote sensing images.* This paper presented the results of the graph-based Best Merge method as an illustration.

Recent *operational remote sensing projects* require the usage of segmentation and *object-based image analysis.* Applications outlined in this paper were the identification of ineligible land on pastures, the observation of red mud spill, ragweed monitoring and the recognition of built infrastructure in rural areas. All of these projects were processed in the same software environment with similar processing methods.

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