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Edge- and region-based segmentation technique for the extraction of large, man-made objects in high-resolution satellite imagery

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Abstract

A new object-oriented segmentation approach with special focus on shape analysis was developed for the extraction of large, man-made objects, especially agricultural fields, in high-resolution panchromatic satellite imagery. The approach, a combination of region- and edge-based techniques, includes new methods for the evaluation of straight edges, edge preserving degradation, and edge-guided region growing.
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Keywords: Object recognition; Image segmentation; Straight edge extraction; Edge preserving smoothing; Region growing

1. Introduction

Automatic image analysis of natural scenes has always been a challenging task. This is especially true for the analysis of remote sensing data where, e.g. sensor characteristics and varying atmospherical conditions influence the quality of the imagery. However, the visible objects in these images such as houses, streets, or agricultural fields are important data for Geographical Information Systems (GIS) which are widely used by public authorities and other institutions as a tool for decision-making and planning. Some GIS applications, e.g. the monitoring of land-cover classes or the assessment of damages after natural disasters, depend on the precise detection of the boundaries of agricultural fields. Only recently, new satellite sensors such as IKONOS or QuickBird provide image data with a ground sampling distance in the panchromatic band of up to 1 or 0.7 m, respectively, a sufficient spatial resolution for the desired tasks.

Due to the complexity of object characteristics, the extraction of field boundaries in high-resolution imagery requires sophisticated methods that are able to identify each agricultural field with exact boundaries as a single unit despite superfluous details and possibly low contrast to neighboring regions. In this context, it was necessary to develop a new segmentation technique with special emphasis on the consideration of shape information which will be presented in this paper.

2. Task and model definition

If large regions with anthropogenic influence, such as agricultural fields, are to be detected automatically within data of high spatial resolution (Fig. 1(a)), there exist three main difficulties:

1. many small details can cause high-gray value variations within the objects which result in over-segmentation;
2. the brightness contrast to neighboring objects can be low which is responsible for under-segmentation; and
3. complex geometric shapes with long straight boundary parts that are not necessarily rectangular prevent the use of fixed geometric models.

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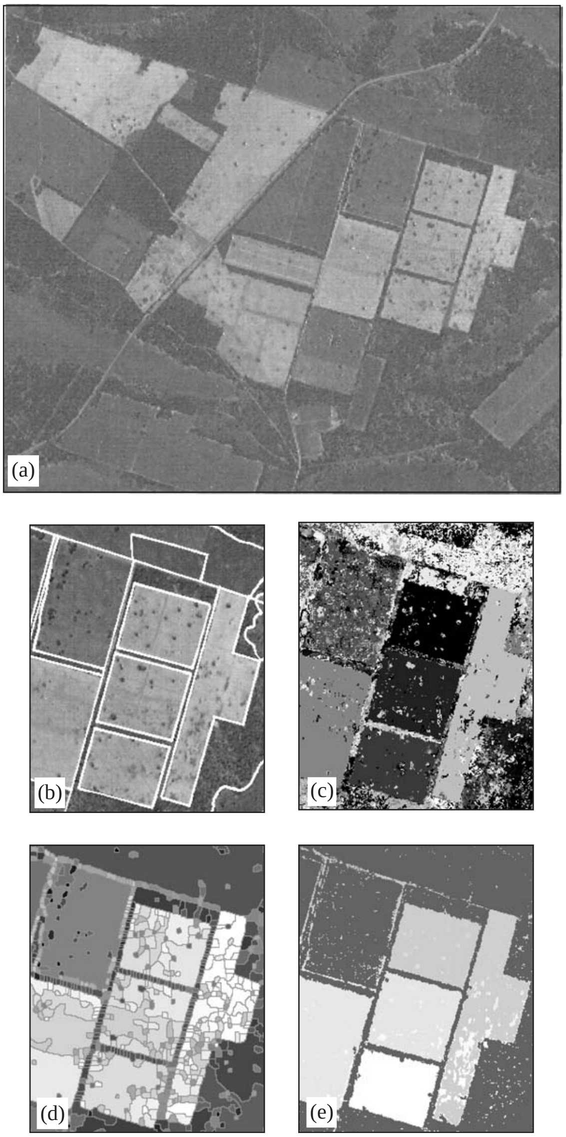

Fig. 1. Example of the complexity of object characteristics within the given image data (MOMS-02, panchromatic band, spatial resolution 4.5 m) and the difficulties of standard segmentation techniques: (a) Farmland in Zimbabwe with agricultural fields of different shape, size, albedo, and details within the field boundaries. (b)–(e) segmentation results of a subset of (a): (b) segment boundaries (in white) of a manual segmentation performed by a human expert, (c) resulting segments of an ISODATA clustering in five classes, each segment separated by a different gray value, (d) segments of a watershed segmentation which was applied on an amplitude image of the smoothed original, (e) segments of a region growing algorithm.

The consequences of these problems become obvious in the results of standard segmentation techniques such as ISODATA clustering [1], region growing [1], or watershed algorithms [2] in comparison with the segmentation by a human expert (Fig. 1(b)–(e)). These automatically generated segmentations are either highly over-segmented or additionally under-segmented. The desired objects have to be reconstructed using a suitable model; however, the unknown object geometry complicates the identification of appropriate split or merge rules.

Therefore, as basis of this work, the assumed object model is defined as follows: the objects are ideally large and rather homogeneous areas with respect to the gray-value intensities. Object boundaries are defined by a high brightness contrast to neighboring regions and/or a typically long and straight object shape. This shape criterion is of special importance at border segments where low contrast is present.

3. Segmentation technique

The described model is optimally realized by an approach that combines edge- and region-based methods. Edge-based methods are able to detect long, straight edges while gaps within these edges can be closed by means of region-based approaches. Region-based techniques can determine the homogeneity of objects while uncertainties in detecting the exact boundary positions can be reduced by previously extracted edges. There exist a number of approaches that propose a variety of different possibilities to combine edge- and region-based techniques, e.g. to compute regions and edges separately and fuse the information in further steps [3–6], or to calculate edges or regions using directly the complementary information [7–9]. However, since shape is an essential feature of the given object model, edge information should be incorporated already within the region-based segmentation part. Yet, all the existing techniques based on this strategy [10–13] still only use information about edge positions but no shape information. Therefore, straight edges with low contrast will not be identified as significant boundaries resulting in undesired merges of regions. Within the commercially available program eCognition, developed by Definiens Imaging [14], a segmentation technique is applied where spectral and shape information guide a region merging process. Yet, the shape parameters that are applied to influence the segmentation process relate to the shape of the complete region but not to the straightness of specific parts of the region boundary. Thus, if the spectral contrast of straight boundary lines is rather low, a fusion of adjacent regions is still likely despite a separating straight line.

Therefore, a segmentation technique was developed that preserves and extracts straight region boundaries while suppressing superfluous image details. This method is divided into two main parts (Fig. 2): (1) extraction of model-edges and (2) edge-guided, region-based segmentation.

3.1. Extraction of model-edges

This first main part consists of three different steps. First, edge candidates are extracted at multiple scales to

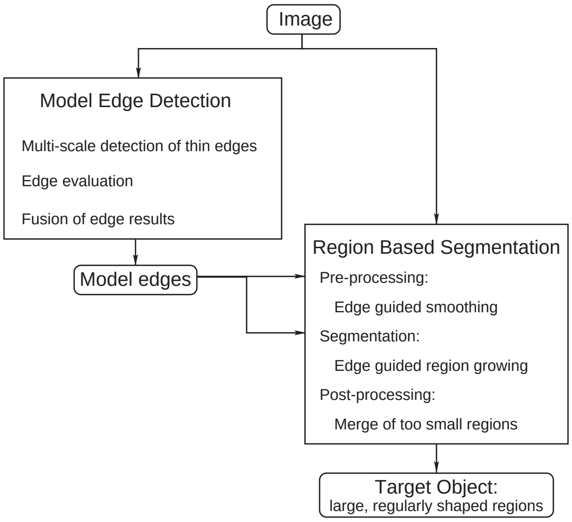

Fig. 2. Scheme of edge and region-based image segmentation for the extraction of large, man-made objects.

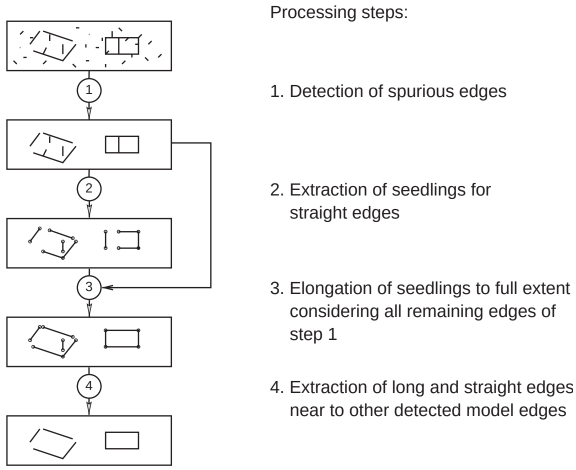

Fig. 3. Method for the detection of model-edges at one scale.

guarantee the detection of all important model-edges. Within the second step, the edges of each scale are evaluated according to the given edge model and the ones that fulfill the necessary criteria are fused to the final edge result in the third and last step. Within this paper only the edge evaluation will be presented in more detail. Further information about the edge extraction at multiple scales and the fusion of model-edges in the final step of this first main part can be found in Mueller et al. [15].

Due to the demanded precision in many applications, edges need to be detected as close to their original position as possible. However, existing approaches for the detection of long, straight lines [16,17] do not fulfill this requirement since they replace the original edges by an approximation based on straight lines. Therefore, a new algorithm was developed that maintains the edges in their original shape and position during the edge evaluation process. The different processing steps for edge evaluation are as follows (Fig. 3).

Before each individual edge segment can be evaluated, some pre-processing is necessary (step 1). Spurious edges are removed by defining a minimum length for all line segments. Furthermore, as we are looking for straight lines, we need a measure for straightness. In this approach, we use a measure which is based on the angle γ in a triangle opened by the edge pixel P and its nth right (R) and left (L) neighbor on the edge segment. The angle γ is defined by the standard equation for computing triangles with three given sides:

$$\gamma = a\cos\frac{a^2+b^2-c^2}{2ab}$$

with $a = \mathrm{PL}$, $b = \mathrm{PR}$, $c = \mathrm{LR}$ representing the length of the sides in the triangle. In comparison to the measures developed by, e.g. Pavlidis and Liow [5], the angle measure allows a more direct interpretation of the values due to a fixed range between 0° and 180° where 180° represents an absolutely straight line.

After the elimination of spurious edges in step 1, a line-following algorithm divides the edges into small parts for further analysis (step 2) using the angle measure with a defined threshold and additional 1-D Gaussian smoothing for the precise detection of sharp-bending (SB) points. Each small edge part is evaluated whether it already fulfills some minimum model-edge criteria. Edge segments that fulfill these criteria are called *seedlings*, since they are the basis for the search for more elongated straight lines in the third processing step. Seedlings are defined in the following way:

- *strength*: they have to possess a minimum edge contrast which is necessary to distinguish between significant and randomly straight edges. Randomly straight edges can occur throughout the entire image but they are generally characterized by low contrast;
- *straightness*: i.e. they must have an angle value higher than a specified minimum threshold;
- *length*: they should be already rather long, otherwise the angle measure is not significant.

Starting at end points of extracted seedlings, straight continuations are searched in the whole, pre-processed set of edge segments detected at this scale. In order to decide whether a candidate segment at the end of a seedling is a plausible elongation, the pixels of the candidate segment have to be within a tolerable distance to the approximated straight line of the seedling. The elongation process is iterated for each seedling until no further continuation is possible. In a fourth and final step, only the straight lines having at least a certain minimum length and proximity to other edges are extracted as important boundaries of essential image structures.

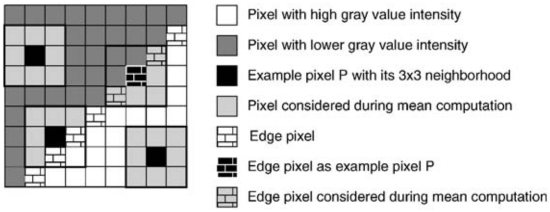

Fig. 4. Only pixels in gray are considered for the computation of the mean value of each center pixel.

3.2. Edge-guided region-based segmentation

The second part of the presented approach is divided into three separate steps (Fig. 2):

1. pre-processing of the original image by an edge-guided smoothing technique to eliminate noise and superfluous structures and to homogenize larger objects within their boundaries;
2. image segmentation realized by an edge-guided region growing technique;
3. post-processing in order to merge (based on gray-value similarity, [10]) small segments to the required larger regions of the object model.

The information provided by the extracted edges of the first part is used within steps (1) and (2). For this purpose, new methods for an edge preserving smoothing and a shape and edge oriented region growing had to be developed. These steps are explained in more detail in the following sections.

3.2.1. Edge-guided smoothing

There are a number of techniques that are designed to preserve edges while smoothing homogeneous regions, e.g. the anisotropic diffusion by Perona and Malik [18], morphological operators such as the median, or other non-linear smoothing filters [19–21]. However, they lead to an emphasis of small, but contrasting structures instead of their elimination. Additionally, edges with low contrast can be smoothed instead of being preserved although they might be significant boundary parts. Furthermore, a homogenization of larger objects is usually not possible without altering the shape of the object boundaries, e.g. at corners. Therefore, a new method for edge-controlled smoothing had to be developed. It is a combination of a diffusion process and an edge-guided mean value computation. Similar to a diffusion process, several iterations are calculated to realize the distribution of a potential represented by the image gray values. In each iteration, a 3×3 filter matrix is used for a biased mean-value computation. Only these pixels of the eight neighbors of pixel P that are on the same side of the edge as P are considered in the mean-value processing (Fig. 4). Edge pixels themselves are defined to belong to the region with the higher gray-value intensity in this process.

3.2.2. Edge-guided region growing

The reason for the choice of a region growing algorithm as the region-based segmentation technique is that it allows a precise control of the region formation process. The basic technique usually considers only homogeneity conditions such as the distance between the pixel's gray-value intensity and the mean gray value of the currently growing region R. In this approach, this criterion is extended by two edge, respectively, shape conditions:

Pixel P does not belong to R, if (1) P lies on the opposite side of an edge, (2) P is localized within a bottleneck part of a growing region, i.e. it grows through a small gap between detected model-edges or region boundaries.

The first of the two rules prevents a region from growing over edges that were already extracted (Fig. 5(a) and (b)). The second criterion is important to close gaps in edges (Fig. 5(c) and (d)). If the number of region candidates that grow on one side of the current region falls beneath a given threshold *bnt* (**b**ottle**n**eck**t**hreshold) then the region grows through a gap between edges or through a bottleneck between already grown regions. Therefore, the growing process has to be stopped at this position.

4. Results

The technique was tested on images from four different sensors with different spatial resolution (MOMS-02: 4.5 m; IRS-C: 5.8 m; IKONOS: 1 m; aerial imagery: 1 m after digitalization). The test areas are primarily located in agricultural regions in Zimbabwe and Germany, but an urban example is presented as well. In the following section, the results and comparisons to other methods are presented while Section 4.2 focuses on the important question of parameter selection. An other application to urban areas can be found in [22].

4.1. Examples and comparison

Fig. 6 comprises the results of the different processing steps for the example of Fig. 1(a) while Fig. 7 presents the results of a test site in Germany that was acquired by the IRS-C sensor. The resulting model-edges in Figs. 6(a) and 7(b) demonstrate the ability of the new approach to detect long straight edges. Gaps within straight object boundaries result from extremely low or practically non-existent edge contrast. Some superfluous straight edges within the objects are extracted due to their too high contrast which lead to undesired subdivisions of large objects within the region growing result (Figs. 6(c) and 7(d)). Only a small number of these generated subregions also remain in the final segmentation result if they already fulfill the final size condition (Figs. 6(d) and 7(e)). In Fig. 8 further segmentation

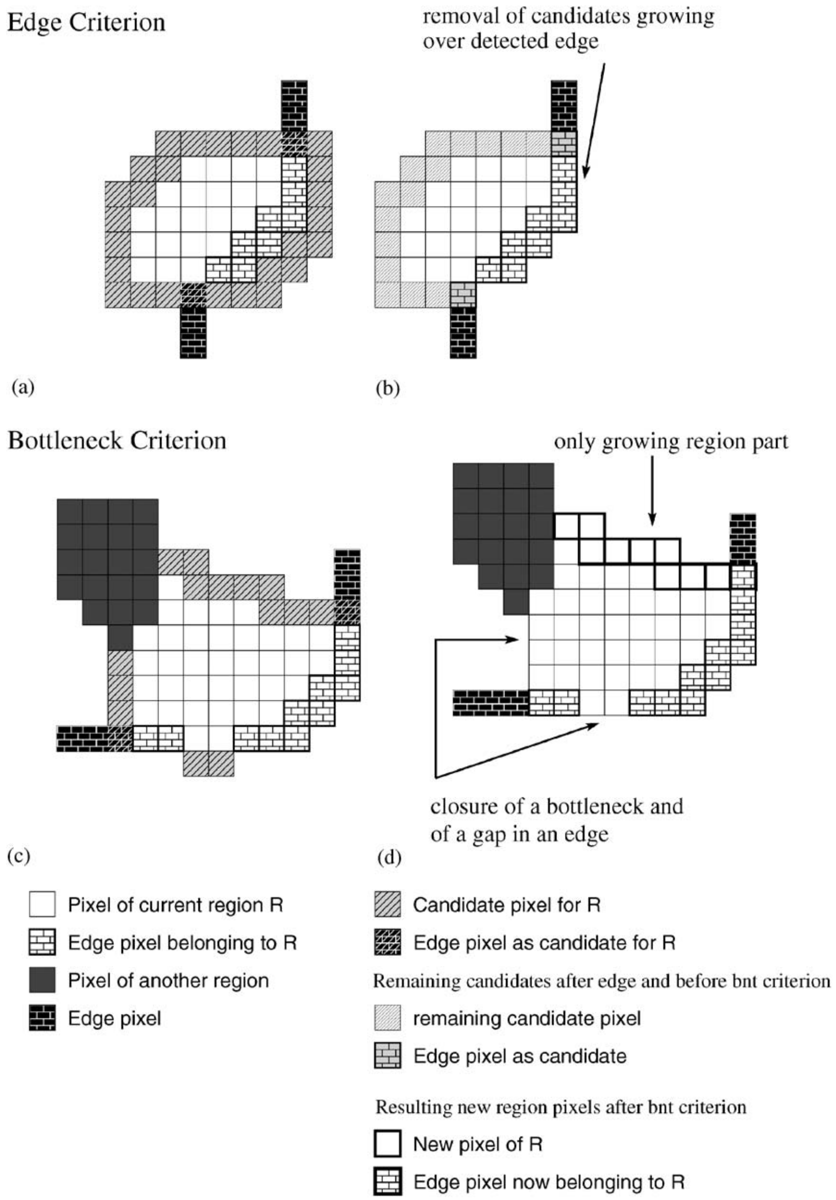

Fig. 5. New region growing criteria. Examples of region growing situations before (a) and after (b) applying the new edge criterion as well as before (c) and after (d) the use of the bottleneck condition.

examples are presented, demonstrating not only the ability of the method to cope with different sensor types, recording conditions and spatial resolutions, but also its potential to adapt to different fields of application.

For comparison, two techniques were chosen—the mean shift algorithm [9] and eCognition [14]—due to their availability as free software (in the latter case at least as trial version). The results of two of the possible three segmentation classes of the mean-shift program (Fig. 9) clearly demonstrate that the algorithm still exhibits the same problems as the standard algorithms that were described in Section 2. The segmentation in Fig. 9(a) is clearly too detailed for the desired large objects. Many segments of Fig. 9(b) are still too detailed while for a large number of objects important boundary parts are missing due to their low contrast. Therefore, these objects are already merged with other regions. The segmentations resulting from eCognition (Fig. 10) are far more promising, proving the potential of approaches that

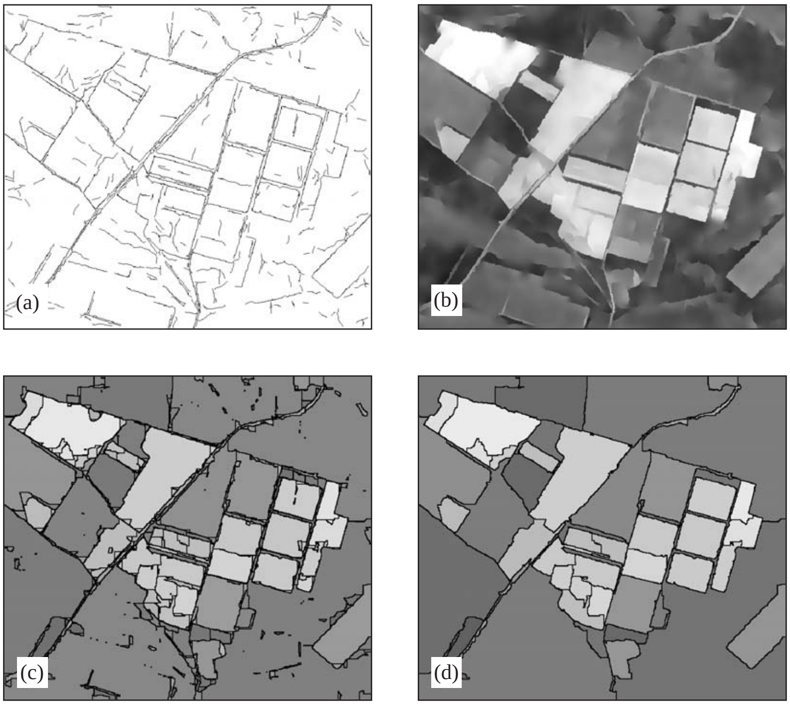

Fig. 6. Results of the different processing steps for the test scene of Fig. 1(a): (a) detected model-edges, (b) smoothed image, (c) result of edge-guided region growing, (d) result after merge of small regions.

take into account not only spectral, but also shape information. The dotted white square in Fig. 10 even shows an example where eCognition extracts at least half of a dark segment that was not detected at all by the presented approach (due to an undetected straight edge part of the upper boundary). However, problems remain in eCognition at a number of other object boundaries with low contrast. Fig. 10(a) represents an example of an over-segmentation that already contains undesired merges of neighboring objects or parts of them due to the discontinuations of straight lines of low contrast (solid and dotted square). In Fig. 10(b), the scale is nearly as high as necessary for the extraction of large objects. Additionally, the weight on the shape parameters was increased, thus solving the problem of discontinuation in the dotted square. However, the problem in the solid square still persists and additional merges occur, e.g. within the dashed square. Up to now, eCognition still lacks the possibility for a consideration of specially shaped boundary parts of low contrast.

4.2. Parameter selection

Throughout the approach, several parameters and thresholds needed to be defined. Most of these parameters are image independent because they describe constant features of straight lines. Table 1 lists all image independent parameters of the presented technique with their default values. Similar to general applications tools like eCognition, some parameters need to be image dependent to allow the adaptation to spatial variations (different spatial resolution of the sensor, different object sizes due to different geographic location, different type of application) as well as different recording conditions (different degree of noise). Aerial image data, e.g. display a lower degree of noise than MOMS or IRS data, therefore, the minimum amplitude for seedlings can be reduced and less smoothing is necessary. For IKONOS image data with their possible 11-bit data range, the tolerance for the region growing gray-value condition needs to be increased. Table 2 summarizes the image-dependent parameters and lists the ranges of values for the examples of this paper.

5. Conclusion and outlook

A new approach for the extraction of large, man-made objects in satellite image data was developed and presented in this paper. The key information for this task is shape knowledge. Its inclusion is necessary due to a high amount of superfluous details within objects and especially a low contrast between adjacent objects in the image data. Thus, the technique is divided into two parts where

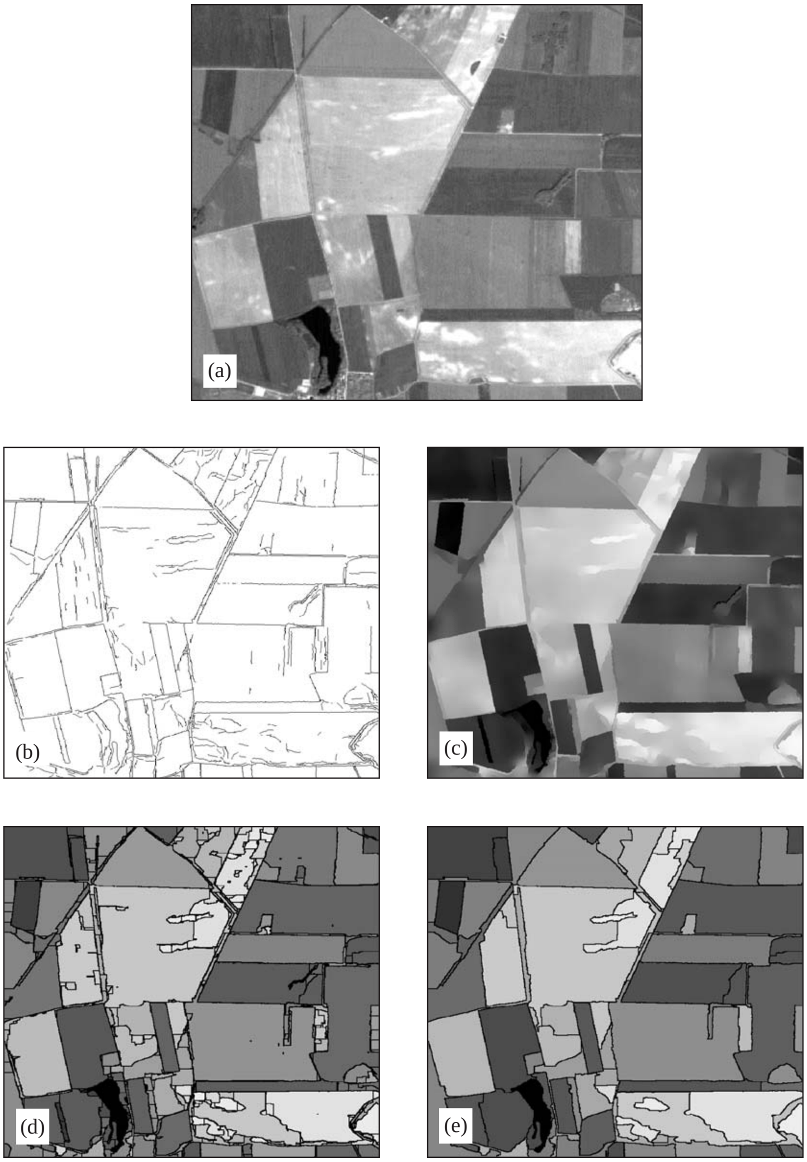

Fig. 7. Results of the different processing steps for a test scene of agricultural fields in Germany recorded by the IRS-C sensor. (a) Original image, (b) detected model-edges, (c) smoothed image, (d) result of edge-guided region growing, (e) result after merge of small regions.

essential shape information is extracted in the first part to control a new region growing algorithm in the second part. The results demonstrate first of all the ability of the presented approach to detect long straight edges in images at their precise position, although, e.g. an improved decision between important object boundaries and randomly straight edges is still necessary. Second, and most important, regions with regular shape such as agricultural fields can be extracted in high-resolution panchromatic image due to the new edge-guided technique. Comparisons with standard methods demonstrated the advantages of the presented method. Only another object-oriented approach that is realized by the eCognition Software, achieves nearly similar results, but still lacks possibilities to control the segmentation process based on straight region boundaries of low contrast. Future work is focused on the integration of multitemporal and multispectral image data to solve decision problems within the segmentation process originating from the limited information in one panchromatic band.

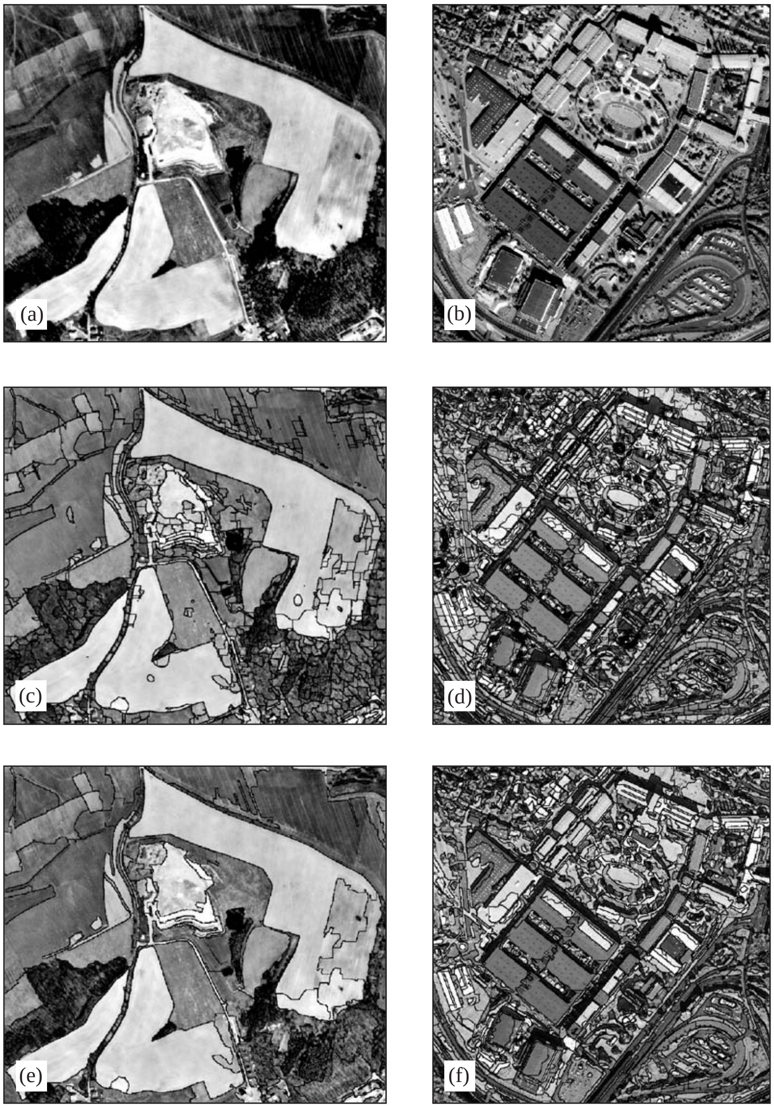

Fig. 8. Further segmentation results. (a) Aerial image of agricultural fields in Germany, (b) IKONOS scene of Berlin, Germany, (c) and (d) results of the edge guided region growing for (a) and (b), (e) and (f) final results after merge of small regions.

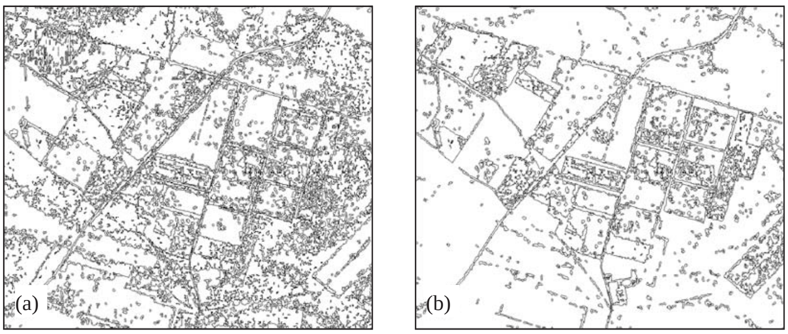

Fig. 9. Result of applying the mean-shift algorithm [9] to Fig. 1(a). (a) Result using the segmentation class of the program code with intermediate resolution (over-segmentation), (b) result using the segmentation class with the lowest resolution (under-segmentation).

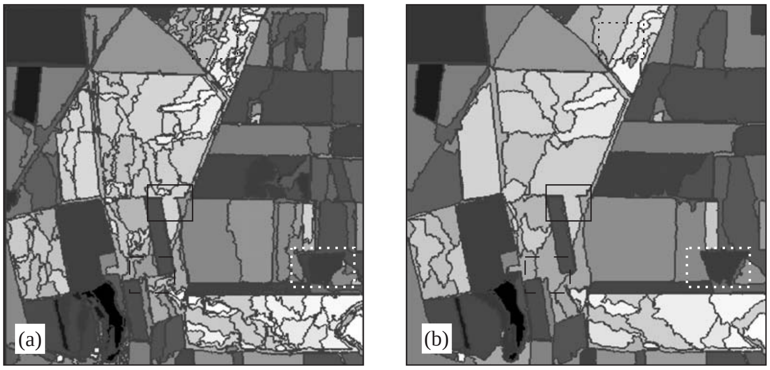

Fig. 10. Result of eCognition applied to Fig. 7(a). (a) Example of over-segmentation with insufficient emphasis on shape information, (b) example of less over-segmented objects (higher scale value) and increased weight on shape parameters. Solid, dotted, and dashed squares indicate examples of problematic, i.e. low contrast, boundary parts.

Table 1
Default values of image-independent parameters

Image-independent parameters	Default values
Edge extraction	
Scale parameter	10 scales: $\sigma = 0.8$–3.95, $\Delta\sigma = 0.35$
Edge evaluation—step 1	
Minimum length of edges	5 pixels
Edge evaluation—step 2	
Distance to neighboring points in angle measure	7 pixels
Angle for SB points	140°
Minimum seedlings angle	160°
Minimum seedlings length	10 pixels
Edge evaluation—step 3	
Mean distance	$\leqslant 2$ pixels
Minimum percentage for straight continuation	50%
Edge evaluation—step 4	
Proximity to other edges	Within a radius of 3 pixels around end points
Edge-guided region growing	
Bottleneck threshold	20 pixel for closing gaps of 5 pixels independently of growing direction

Table 2
Value ranges of image-dependent parameters for the presented applications

Parameter	Range
Edge evaluation—step 2	
Minimum strength of seedling	5–15% of absolute maximum in amplitude image
Edge evaluation—step 4	
Minimum length	15–25 pixels
Edge-guided smoothing	
Number of iterations	50–200
Edge-guided region growing	
Tolerance	10–40 digital numbers (DN)
Region merge	
Minimum size of final regions	1000–5000 pixels, exception: small regions (100–500 pixels) with very high contrast (30–60 DN) to neighboring regions

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