SEGMENTATION OF HIGH-RESOLUTION REMOTELY SENSED DATA - CONCEPTS, APPLICATIONS AND PROBLEMS

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ABSTRACT:

Segmentation algorithms have already been recognized as a valuable and complementary approach that similar to human operators perform a region-based rather than a point-based evaluation of high-resolution and multi-source remotely sensed data. Goal of this paper is to summarize the state-of-the-art of respective segmentation methods by describing the underlying concepts which are rather complex in the case of processing remotely sensed data, demonstrating various applications (automatical object recognition, signal-based fusion as support for visual interpretation, and estimation of the terrain surface from Digital Surface Models), and identifying yet existing problems and further research and development needs.

1. INTRODUCTION

Remote sensing data are an important source for generating or updating GIS databases in a variety of applications. As a reaction to the limitations of the available data sources with respect to their spatial resolution and inherent information content, in the last ten years the focus was laid on the development of advanced sensors, for instance laser scanners (presently, about 65 operational airborne systems world-wide), radar-interferometric sensors (e.g., the Shuttle Radar Topographic Mission), or electro-optical cameras with in-flight-stereo capabilities (e.g., airborne systems like ADS 40, DMC or HRSC-A, and spaceborne systems like Ikonos or Quickbird). In order to increase the information potential for interpretation purposes, multi-sensor systems have been developed for the simultaneous acquisition of image and elevation data (e.g., the TopoSys II sensor).

However, with these sensors the user community faces new problems in the automatical analysis of these types of data:

1. The high spatial resolution of the advanced sensors increases the spectral within-field variability - in contrast to the integration effect of earlier sensors - and therefore may decrease the classification accuracy of traditional methods on per-pixel basis (like the Maximum-Likelihood method). Hence, novel and efficient analysis techniques become a mandatory requirement for efficient processing and analysis.
2. The availability of multi-sensoral or even multi-source data (e.g., existing information from Geographical Information Systems, GIS) is strongly correlated with the necessity for a fusion on data but in particular on feature or decision level (Pohl & van Genderen, 1998). Unfortunately, many standard techniques are not able to handle heterogeneous data sources and context information.

In this context, segmentation algorithms have already been recognized as a valuable and complementary approach that - similar to human operators - create regions instead of points or pixels as carriers of features which are then introduced into the classification stage. The conceptual idea is that each of these regions corresponds exactly to one and only one object class (object oriented approach). Furthermore, segmentation algorithms are able to handle multiple data and information sources, thus performing a fusion on feature level.

Goal of this paper is to summarize the state-of-the-art of the use of segmentation algorithms for various processes applied to remotely sensed data by describing the underlying concepts which are rather complex in this case (chapter 2), demonstrating various applications as carried out at our institute (automatical object recognition, signal-based fusion as support for visual interpretation, and estimation of the terrain surface from Digital Surface Models; chapter 3) and identifying yet existing problems and further research and development needs (chapter 4).

2. CONCEPTS OF SEGMENTATION ALGORITHMS

Segmentation is the process of completely partitioning a scene (e.g., a remote sensing image) into non-overlapping regions (segments) in scene space (e.g., image space).

Respective algorithms have been developed within Pattern Recognition and Computer Vision since the 1980's with successful applications in disciplines like medicines or telecommunication engineering. However, due to the complexity of the underlying object models and the heterogeneity of the sensor data in use, their application in the fields of Remote Sensing and photogrammetry was limited to special purpose implementations only. With the advent of high-resolution as well as multi-source data sources the general interest in segmentation methods has become evident again, and at last significant progress in terms of user awareness was achieved with the introduction of the first commercial and operational software product (*eCognition* by Definiens-Imaging) in the year 2000.

In the following we will briefly describe the general concepts of segmentation methods (section 2.1) and will emphasize the particularities for the evaluation of remotely sensed data (section 2.2).

2.1 General concepts

2.1.1 Principles and strategies: Basic task of segmentation algorithms is the merge of (image) elements based on homogeneity parameters or on the differentiation to neighbouring regions (heterogeneity), respectively. Thus, segmentation methods follow the two strongly correlated *principles of neighbourhood* and *value similarity*.

Generally the following strategies for partitioning a scene into regions are distinguished:

- point-based
- edge-based
- region-based
- combined

Point-based approaches are searching for homogeneous elements within the entire scene by applying global threshold operations which combine such data points that show an equal or at least similar signal or feature value. This threshold can divide the feature space into two or more parts (binarization or generation of equidensites, resp.). The choice of threshold values can be performed statically or dynamically based on histogram information.

Because this grouping has not considered the principle of neighbourhood so far, a connection analysis in scene space is performed in a second step. Here, spatially connected elements (components) of equal value (e.g., grey value "1") are grouped to one region (*component labeling*).

It has to be noted that point-based approaches are less suitable for the evaluation of remotely sensed data due to varying reflection values for a certain object placed at different locations within the real world and the sensed scene (as an example see figure 1, middle).

Edge-based approaches describe the segments by their outlines. These are generated through an edge detection (e.g., a Sobel filtering) followed by a contour generating algorithm. Optionally, the transition from the outlines to the interior region can be achieved by contour filling methods like the watershed algorithm.

As figure 1 (right) demonstrates, the main disadvantage of edge-based approaches is that the edge and also the contour image is strongly affected by noise (in particular in wooded regions, less crucial for artificial objects) which may lead to an unacceptable over-segmentation.

Region-based approaches start in the scene space where the available elements (pixels or already existing regions) are tested for similarity against other elements (see section 2.1.2). Concerning the definition of the initial segmentation the procedures of *region growing* (bottom-up, i.e. starting with a seed pixel) and *region splitting* (top-down, i.e. starting with the entire scene) are distinguished. One disadvantage of the splitting method is that it tends to an over-segmentation because a splitting always produces a fixed number of sub-regions (normally: 4) although two or three of them might actually be homogeneous with respect to each other. As a consequence, one can apply a method combination which leads to the *split-and-merge* algorithm that after every split tests whether neighbouring regions are so similar that they should be re-merged again.

In the following explanations and applications we will mainly rely on region growing approaches.

2.1.2 Homogeneity criteria: In the following the realization of the *principle of value similarity* (or homogeneity, resp.) will be discussed more in detail. Given two elements A and B (i.e. pixels or regions) one possibility for deriving a *homogeneity measure* is to compare a certain feature of A and B (e.g., the grey value) through its Euclidian distance. In addition, it is also possible to consider simultaneously multiple features f_i (i=1, ..., n) of A and B, with the option to introduce individual weights g_i. Hence, a fusion on feature level is realized which gives the corresponding heterogeneity measure Δh by:

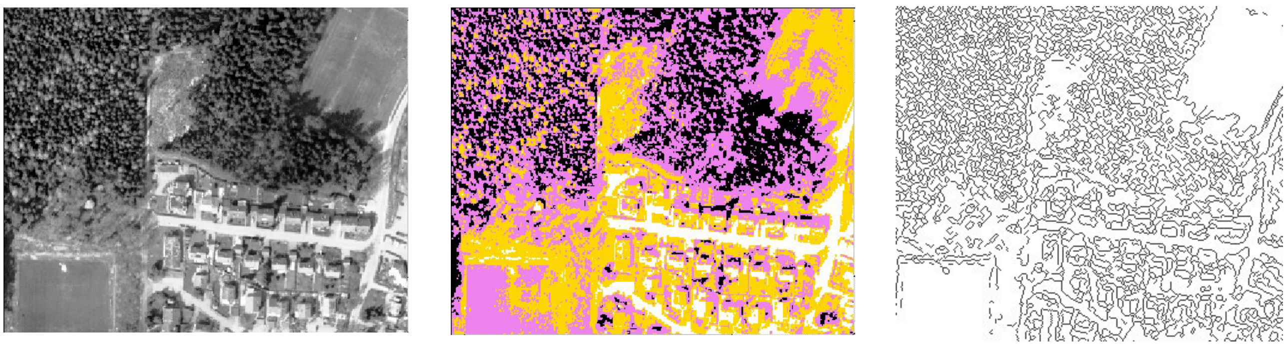

Figure 1. Given image (left) and exemplary point-based segmentation with four classes (middle), and contours as input for edge-based segmentation (right) - data courtesy of TopoSys GmbH -

$$\Delta h = +\sqrt{\sum_{i=1}^{n} g_i \cdot (f_{A,i} - f_{B,i})^2} \qquad (1)$$

As an alternative, the homogeneity measures can be computed before and after an eventual merge of the elements A and B.

With the obtained measure Δh it can be decided whether the elements A and B have to be merged to a larger segment or not. This is done by a comparison with a threshold that controls the size and number of segments and with that the level of generalization of the segmentation process (see also section 2.1.3).

The merging algorithm can also consider further constraints concerning neighbourhood and similarity: In the simplest case element A accepts B if the homogeneity measure is below the given threshold (*fitting*). In contrast, A may accept only that neighbouring element B which fulfills the homogeneity criterion best (*best fitting*). Furthermore an element C is connected to A (which is similar enough to B) only if B and C as well as A and C are similar enough (*local mutual best fitting*).

2.1.3 Evaluation of segmentation: In general the described segmentation methods do not yield a perfect partition of the scene but produce either too much and small regions (*over-segmentation*) or too less and large segments (*under-segmentation*). The first effect is normally a minor problem because in the following classification step neighbouring segments can be attached to the same category a posteriori.

Applying segmentation methods to remotely sensed data we can observe that over- and under -segmentation can occur within a single scene depending on the heterogeneity of objects under consideration. As figure 2 shows, natural objects tend to be stronger partitioned than regular artificial objects. Furthermore, different levels of generalization are desired depending on the specific applications (e.g., evaluation scales). For instance, some applications may demand for the delineation of single trees while others need larger wooded areas.

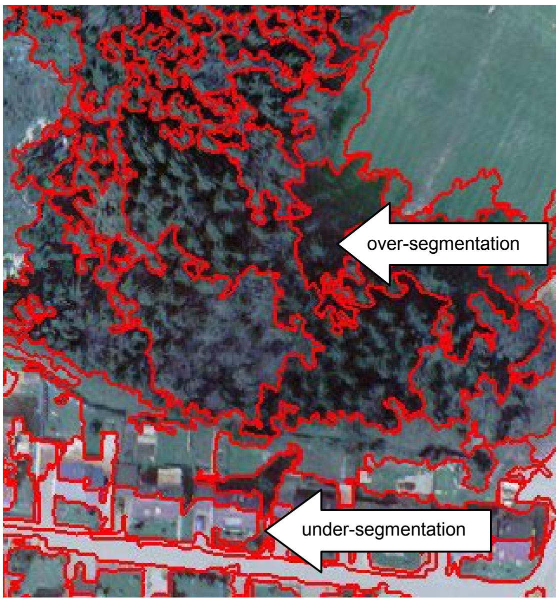

Figure 2. Simultaneous over- and under-segmentation within a remote sensing scene - data courtesy of TopoSys GmbH –

Methods for the evaluation of segmentation results are discussed for example by Hoover et al. (1996), Zhang (1996) or Levine & Nazif (1985). In the last case the authors also present developments for a dynamical determination of the segmentation quality by continuously computing homogeneity measures of all intermediate regions. However, it has be noted that presently the most reliable evaluation method is still a visual interpretation that has to consider the exact geometrical position of the segment borders as well as the membership of one and only one object class to a single region. However, with that the generalization level as well as the homogeneity features and parameters are controlled in a rather subjective manner.

2.2 Particularities for evaluating remotely sensed data

Numerous segmentation methods have already been developed for various applications, including medicines, telecommunication engineering or the analysis of dynamic scenes in neuro-informatics. Consequently, the available software products are originating from these or similar disciplines.

As already mentioned at some places in section 2.1 several reasons lead to the fact that existing methods and implementations from these disciplines can not be directly transferred to the domain of remote sensing, in particular:

- Remote sensing sensors are producing multi-spectral, sometimes also multi-scale input data, so that in contrast to the most often used panchromatic and monoscopic image data in the disciplines mentioned above not only the complexity but also the redundancy increases.
- Manifold additional data (e.g., GIS or elevation data) are available.
- In contrast to other applications various objects of heterogeneous properties with respect to size, form, spectral behaviour, etc. have to be considered.
- General multi-scale evaluation tools have not been developed. They exist only for some limited areas, for instance for the extraction of roads from aerial imagery (Ebner et al. 1998).
- In contrast to other applications a model-based interpretation is much more difficult due to the heterogeneity of the inherent object classes;

Hence, segmentation algorithms have been introduced relatively late for the analysis of remotely sensed data (e.g., Ryherd & Woodcock 1996). As a consequence, the first commercial software packages were introduced not before the year 2000, for example the *Stand Delineation Tool* of the Finnish company Arboreal for forest inventory purposes (Arboreal, 2002) or *eCognition* (Definiens-Imaging 2002) that aims at a more general use.

In conclusion segmentation approaches for the evaluation of remotely sensed data have to be rather complex systems that should

- handle various input data simultaneously (*multi-source aspect*)
- integrate a couple of segmentation strategies serving for all object types which shall be extracted (*multi-method aspect*)
- create various levels of generalization at the same time - due to the fact that different objects are represented best at

different scales (*multi-scale aspect*).

3. APPLICATIONS

In the following we will give an insight into the various applications of segmentation methods with respect to the evaluation of remotely sensed data - also considering the above mentioned specific aspects. Not surprisingly, the emphasis of the usage is on automatical object recognition tasks (section 3.1), but we will also demonstrate alternative applications such as signal-based fusions for visual interpretation purposes (section 3.2), and the terrain surface estimation from Digital Surface Models (section 3.3).

3.1 Automatical object recognition

3.1.1 Brief overview: A couple of scientific work has been undertaken on the use of segmentation methods for the extraction of certain features from close range photogrammetric imagery on one hand, and for the detection of object classes from multi-spectral or panchromatic imagery, for example considering buildings (e.g., Brenner, 2000), buildings and roads (Hoffmann, 2001), or airports (McKeown et al., 1985). Only a limited number of work is concerned with a more detailed classification, for instance Bauer & Steinnocher (2001) perform a recognition of 11 object classes in an urban scene.

3.1.2 Biotope monitoring project: A concrete project at our institute had the purpose to test the applicability of data of the High Resolution Stereo Camera–Airborne (HRSC-A; Wewel et al. 1998) for the classification of biotope types on reaches of Federal waterways characterized by strong relief features. The data are based on a flight mission along a reach of the Main-Danube Canal commissioned by the German Federal Institute of Hydrology (BfG), Koblenz. The spatial resolutions amount to 30 cm in the case of the multi-spectral and 200 cm in the case of the Digital Surface Model (DSM) which has been derived by automatical matching (estimated accuracies ± 20 to ± 30 cm in planimetry, ± 50 cm in height. A land use vector data set is available based on a field survey.

Aim of our study is the classification of the land use/land cover in this rural test site. The object catalogue comprises the following classes: channel, cultivated field, bare field, forest, smaller groups of trees, shrubbery and roads. The objects exhibit a large range of different scales ranging from small shrubs to large cultivated fields.

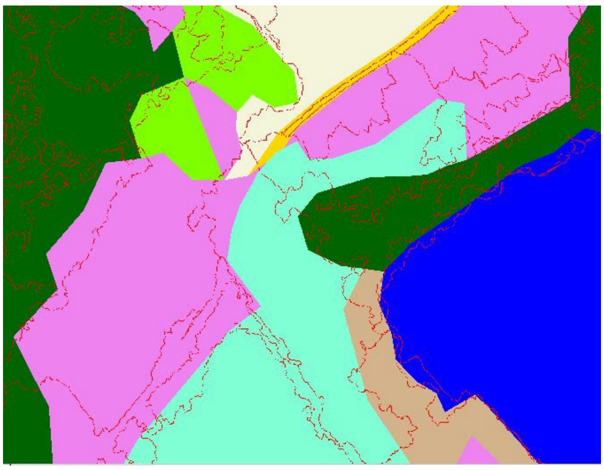

Figure 3. Improved degree of details of segmentation compared to biotope classification based on field survey

Using the hierarchical approach of the *eCognition* software the segmentation is performed at different levels of generalization. The best segmentation results are achieved with different spectral combinations and weighting factors for the different bands with respect to the object classes. As figure 3 demonstrates, a much higher degree of detail could be achieved with the segmentation approach compared to the biotope classification based on the field survey. For a more detailed project description refer to Schiewe et al. (2001).

3.2 Signal-based fusion for visual interpretation

There are a couple of reasons still to deal with aspects of the visual interpretation of imagery. On one hand, most of the (semi-) automatical object recognition procedures do not lead to satisfying results. On the other hand, an increasing number of airborne and spaceborne sensors produce spatially lower resolution but multi-spectral data as well as higher resolution but pan-chromatic data (e.g., Ikonos, Quickbird) so that a signal-based fusion of the above mentioned image data prior to a visual interpretation is very often demanded. Such a fusion shall combine the respective advantages, in particular

- emphasize certain image features (e.g., gradients, colors),
- substitute missing information (e.g., in shadow regions),
- improve geometrical corrections (e.g., by using data of higher geometrical accuracy),
- enable stereoscopic evaluations by merging stereo partners,
- detect changes in multi-temporal data sets.

Unfortunately conventional, point-based operating signal-based fusion methods do not lead to reasonable and sustainable results. One key problem is that a couple of procedures yield a bad color reproduction and a decrease of the global contrast which is mainly due to the neglecting of the fact that the input channels are normally decorrelated to each other. Furthermore important structural information (e.g., edges) get lost very often if multi-spectral and panchromatic imagery are treated in the same manner (Schiewe, 1999).

Our alternative approach which is still under development follows the idea to combine multi-spectral and panchromatic data not point-wise (using global operations) but in a region-based manner applying different and suitable functional models. In a first step, the segmentation partitions the image set based on information about the texture, dominance of certain colors, existence of edges, and high correlation between certain bands.

In the classification step appropriate functional models are attached to the segments according to their specific properties (e.g., contrast). In this context it has been found that additive approaches generally emphasize color information while multiplicative algorithms (e.g., the Brovey transformation) show off structural information (Schiewe, 1999).

3.3 Terrain surface estimation from DSMs

Most elevation evaluation systems (like stereo matching or laserscanning) produce the respective largest values above a position, i.e. a *Digital Surface Model (DSM)*. However, for some applications (e.g., for hydrological modeling) those objects that stand clearly above the terrain surface (e.g., buildings, trees) are not of interest, i.e. the *Digital Terrain Model (DTM)* is required. Furthermore, for object extraction purposes and virtual city modeling the absolute object heights above the terrain surface (i.e., the differences between DSM and DTM) are needed. Because in practise a DTM is not always available, not sufficiently accurate or reliable enough, or too expensive, a substitute has to be estimated (*estimated DTM, eDTM),* i.e. a *normalization* has to take place. For this task a couple of geometrically based algorithms have been developed (for an overview see Schiewe, 2001), but none of them has succeeded to operationality so far due to the limited quality (especially for inclined terrain) and the missing grade of automatization (especially due to abstract thresholds). Thus, an application dependent combination of methods incorporating rather high interactive efforts for controlling and editing are presently applied in practise.

In the following we want to present a novel region-based, multi-scale approach for the task of terrain surface estimation. Firstly, for the segmentation a proper choice of homogeneity criteria has to be applied. Here we follow the hypothesis that regions which have to be reduced to the terrain surface are characterized by strong altitude gradients and curvatures (Schiewe, 2001). By extending the complexity presented so far by additionally introducing multi-spectral or pan-chromatic image data, we have experienced worse segmentation results due to irregular and inaccurate border lines. This effect is mainly due to a strong affection of image data by noise and shadows.

For the interpretation of the obtained segments we apply a *fuzzy logic* classification approach. There are several reasons for introducing partial rather than crisp memberships in this context (e.g., see Cheng, 2002): On one hand the description of the real phenomenon is neither geometrically sharp (e.g., there is no exactly defined border between forest and terrain) nor standardized (e.g., there are no generally accepted instructions for masking out brush, bridges, etc.). On the other hand the limited spatial sampling rates and measurement errors (the latter being mostly unknown) also lead to indeterminate boundaries.

As classification features the mean of altitude gradients (pointing to forest areas) and the 90% percentile of gradients (pointing to steep edges likes in buildings) can be taken into account. In order to handle the problem of flat roofs (i.e., segments with low gradients), we also consider the 90% percentile of gradients of all surrounding segments (referring to a building edge with high gradients). Finally, the mean difference between first and lust pulse laser scanning measurements, if available, can be taken into account for each segment (also pointing to wooded areas and building outlines).

In some cases it is of interest for the generation of the estimated DTM which object type is associated to a non-terrain area. For instance, for hydrological modeling tasks an interpolation within wooded areas is meaningful while for buildings it is not. Hence, an additional separation of buildings from wooded areas in the classification step becomes necessary. Besides the normalized DSM altitude especially the Normalized Difference Vegetation Index (NDVI) or the spectral texture (in pan-chromatic imagery) are meaningful features.

Figure 4 illustrates the processing results after applying the described region-based approach. The multi-sensor data set which covers a settlement near the City of Ravensburg (Germany) consists of simultaneously acquired laserscanning and multi-spectral image data of the TopoSys II sensor (TopoSys, 2002). As an example, the fuzzification result for the feature "mean gradient" demonstrates the desired high membership values of wooded areas to the class of non-terrain areas as well as the necessity of taking also the gradients of surrounding segments of roof regions into account.

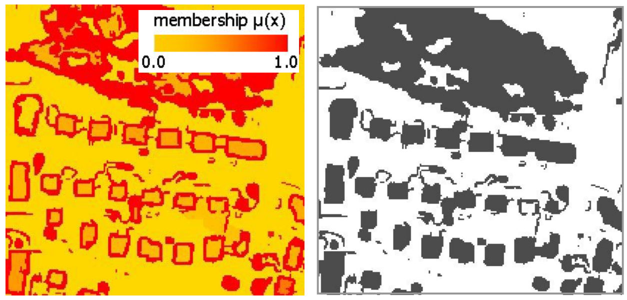

Figure 4. Intermediate results of terrain surface estimation: fuzzification based on "mean gradient" (left) and classification of non-terrain areas (in grey; right) - the test site is identical to that shown in figures 1 and 2

Comparing the achieved results for both tasks - normalization and separation of buildings and other objects - no omission errors have been found. The number of commission errors is below 2% of the entire number of segments. Critical regions within the terrain surface estimation process are small clearings within wooded areas whose slope behaviour in contrast to the surrounding trees could not be sufficiently separated. Applying the segmentation and the following classification not only at one, but at multiple scales, reduces the number of commission errors with decreasing generalization level. However, this scaling process must not be performed as far as possible because the number of omission errors would increase and in the extreme case one would end up with an undesired point-wise classification.

4. PROBLEMS

As already indicated the key problems of an operational use of segmentation algorithms for evaluating remotely sensed data are closely related to the specific aspects as pointed out in section 2.2. While the integration of multi-sensoral and multi-source data is comparably highly developed (with some deficiencies left; see e.g. Schiewe et al., 2001), the realization of the multi-scale and multi-method aspects are yet far away from maturity.

Varying the homogeneity thresholds it is no problem to generate segmentations at different levels of generalization. On the other hand a proper as well as an automatical choice of this level is still not possible and left to an iterative process of visual inspections and modifying the respective parameters. This problem is not only due to missing functionality within the segmentation software products but also to the difficult definition of generalization levels for given applications. It becomes obvious that corresponding work from the cartography domain (e.g., McMaster, 1991; Sester, 2000) has still to be transferred to segmentation algorithms. In particular, rules for the generalization operations of combining (agglomerating) elements have to be taken into account which obviously has to be done in a closed and recursive connection to the classification process.
Concerning the use of different segmentation methods and parameters for delineating different object types it has to be

noted that only little achievements have been made so far. It is obvious that this idea implies a fusion of methods or results. In this context Clement et al. (1993) demonstrate a potential realization which still has to be investigated further and has to be transferred to other applications like the evaluation of high resolution and multi-source data. In order to minimize the complexity of the fusion a selection of a minimum number of significant features should be aimed for. Pinz et al. (1996) present their corresponding concept called *active fusion* that integrates prior knowledge and gives recommendations for the further control of the segmentation process.

In general, it is also desirable to perform the segmentation and the following classification in a hybrid rather in a purely data-driven or model-driven manner. In order to introduce human and GIS-based knowledge respective concepts (e.g., semantical nets) have to be linked to segmentation approaches in order to enable a better control and evaluation of the process.

5. CONCLUSIONS

Traditional multi-spectral classification methods on pixel basis are no longer suited for the evaluation of high-resolution and multi-source data from remote sensing. Region-based approaches consisting of a segmentation and a classification step have already proven to be a satisfying alternative solution.

From a conceptual point of view segmentation algorithms for the evaluation of remotely sensed data have to take into account in particular the availability of multi-source data as well as the need for multi-method and multi-scale functionality in order to model the heterogeneous objects under consideration in a flexible and adaptive way. While a feature level fusion of multi-source data is no severe problem anymore, the other two aspects still need a lot of research and development work.

The huge bandwidth of applications of segmentation approaches that has also been outlined here will certainly lead to further progress which is needed in order to use the full potential of the novel remotely sensed data.

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