A COMPARISON OF SEGMENTATION PROGRAMS FOR HIGH RESOLUTION REMOTE SENSING DATA

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PS ThS9: Uncertainty, Consistency and Accuracy of Data and Imagery

ABSTRACT:

Methods of image segmentation become more and more important in the field of remote sensing image analysis – in particular due to the increasing spatial resolution of imagery. The most important factor for using segmentation techniques is segmentation quality. Thus, a method for evaluating segmentation quality is presented and used to compare results of presently available segmentation programs. Firstly, an overview of the software used is given. Moreover the quality of the individual segmentation results is evaluated based on pan-sharpened multi-spectral IKONOS data. This is done by visual comparison, which is supplemented by a detailed investigation using visual interpreted reference areas. Geometrical segment properties are in the focus of this quantitative evaluation. The results are assessed and discussed. They show the suitability of the tested programs for segmenting very high resolution imagery.

1. INTRODUCTION

Segmentation means the grouping of neighbouring pixels into regions (or segments) based on similarity criteria (digital number, texture). Image objects in remotely sensed imagery are often homogenous and can be delineated by segmentation. Thus, the number of elements as a basis for a following image classification is enormously reduced. The quality of classification is directly affected by segmentation quality. Hence quality assessment of segmentation is in the focus of this evaluation of different presently available segmentation software.

Despite some early research activities (e.g. Kettig & Landgrebe, 1976), image segmentation was established late in the field of remote sensing. First beginning with the availability of very high resolution imagery (< 1 m) and their characteristics (high level of detail, spectral variance etc.) this method has become popular as a common variant of data interpretation.

Recent investigations have shown that a pixel-based analysis of such high resolution imagery has explicit limits. Using segmentation techniques some problems of pixel-based image analysis could be overcome (e.g. Meinel, Neubert & Reder, 2001).

This paper is not related to more mathematical surveys of segmentation, like Haralick & Shapiro (1985) or Pal & Pal (1993). It is rather a more application-oriented comparison based on real remote sensing data.

Among segmentation software there is a growing number of feature extraction programs. In contrast they do not fractionalise the whole image but rather select specific objects from imagery. APEX (PCI Geomatics), FeatureXTR (Hitachi Software Global Technology) or Feature Analyst (Visual Learning Systems) belonging to this group of tools, which are not considered herein.

2. EVALUATED SEGMENTATION SOFTWARE

Recently there exists a multitude of implemented segmentation algorithms for remote sensing tasks, partially having very different characteristics. Only some of them are available commercially. Often they are developed by research institutions or universities. For evaluating capabilities of different algorithms the following programs were compared:

- *eCognition 2.1* resp. *3.0* (Definiens Imaging GmbH, Munich, Germany);
- *Data Dissection Tools* (INCITE, Stirling University, UK);
- *CAESAR 3.1* (N.A.Software Ltd., Liverpool, UK)
- *InfoPACK 1.0* (InfoSAR Ltd., Liverpool, UK);
- *Image segmentation* for Erdas Imagine (USDA Forest Service, Remote Sensing Applications Center, Salt Lake City, USA);
- *Minimum Entropy Approach to Adaptive Image Polygonization* (University of Bonn, Institute of computer science, Bonn, Germany);
- *SPRING 4.0* (National Institute for Space Research, São José dos Campos, Brasilia).

All programs are described in brief in table 1. The choice of approaches was based on the software segmentation suitability for remote sensing imagery. On the other hand cooperativeness of the developers was a precondition for this survey.

3. METHOD

3.1 Used imagery

Pan-sharpened multi-spectral IKONOS data (1 m ground resolution, principle component algorithm) of two test areas were segmented by the software above. Each test area has a size of about 2000 by 2000 Pixel, representing an urban and a rural landscape. The procedure was aimed at the extraction of

Segmentation program	eCognition 2.1 resp. 3.0	Data Dissection Tools	CAESAR 3.1	InfoPACK 1.0	Image Segmentation (for Erdas Imagine)	Minimum Entropy Approach	SPRING 4.0
Fundamentals							
Developer	Definiens Imaging GmbH	INCITE, Stirling University	N.A.Software Ltd.	InfoSAR Ltd.	USDA Forest Service, Remote Sensing Applications Center	University of Bonn, Inst. of Computer Science	National Institute for Space Research
Website	www. definiens-imaging.com	www.incite. org.uk/ projects/	www. nasoftware. co.uk	www. infosar. co.uk	www2. erdas.com/ SupportSite/	www-dbv. informatik. uni-bonn.de/ polyDemo/	www.dpi. inpe.br/ spring
Algorithm	Region growing	Superpara-magnetic clustering	Simulated annealing	Simulated annealing	Region growing	Triangulation	Region growing/ Watershed
Field of application	Remote sensing	Image analysis, statistical physics	Remote sensing, esp. radar data	Remote sensing, esp. radar data	Remote sensing	Polygonization of noisy imagery	Remote sensing
Fundamental reference	Baatz & Schäpe 2000	Ferber & Wörgötter 2000	Cook et al. 1996	Cook et al. 1996	Ruefenacht et al. 2002	Hermes & Buhmann 2001	Bins et al. 1996
Implementation							
State of development	04/2002 resp. 11/2002	10/2002	09/1998	03/2003	02/2002	08/2002	08/2003
Operating system	Win	Win, Linux, Unix, SGI	Linux, Solaris	Linux, Win	Win	Linux	Win, Unix
System environment	Stand-alone	N/a (maybe MatLab)	Stand-alone	Stand-alone	Erdas Imagine	Stand-alone	Stand-alone
Number of parameters	3	3	6	2	2	2	2
Ca. runtime[1,2]	10 min	10 min	N/a (long)	10 min	1,5 h	Several hours	30 min
Reproduce-ability[3]	No resp. yes (ver. 3.0)	No	No	No	No	No	No
Classification support	Yes (Fuzzy Logic, Near. Neighbour)	No	Yes	Yes (Maximum Likelihood)	No	No	Yes
In- and Output							
Max. image size [ca. Pixel][1]	10000 by 10000	4000 by 4000	2000 by 2000	No Limitations	2000 by 2000	2000 by 1500	2000 by 2000
Max. bit depth	32 bit	16 bit	16 bit	64 bit	8 bit	8 bit	8 bit
Input formats	Raster, Shape	Raster (TIFF)	IMG	NetCDF[4]	IMG	Raster	GRIB[4]
Vector output format	Shape	No (external conversion)	No (external conversion)	No (external conversion)	ArcCoverage	No (external conversion)[5]	No (external conversion)[6]
Use of external data	Yes	No	Yes	Yes	Yes	Yes	Ja
Distribution							
Availability	Commercial	Commercial	Out of distribution	Commercial	Freeware	On request	Freeware
Ca. costs[7] (commercial/ research)	14.000 €/ 9.000 € (non-profit) /2.900 €[8]	N/a resp. free (non-profit)	-	8.300 € / 5.800 €	free	-	free

[1] Specification heavily depends on system resources, particularly main memory; [2] for the used imagery (2000 by 2000 Pixel); [3] when image size is modified; [4] convertible from divers raster formats, e.g. GeoTIFF, IMG; [5] Proprietary vector format; [6] Internal vector conversion was not possible; [7] State April 2003; [8] A simplified version (eCognition elements) is available since May 2003 (3500 €)

Table 1. Outline about evaluated segmentation software.

relevant land cover/use object boundaries. The segmentations were produced by the developers – except for eCognition, SPRING and the Erdas Imagine extension ,Image Segmentation'. Thus, optimal segmentation results (e.g. parameter settings) by experts were assured.

Results for the software CAESAR were available only for the rural test area. The segmentations of the ,Minimum Entropy Approach' cover only one fourth of both areas (each 1000 by 1000 Pixel) due to a lack of performance. Except for InfoPACK the segmentations were done in different levels using altered

parameters affecting segment size. When an object was poorly segmented, coarser or finer segmentation levels could be used.

3.2 Pre-processing of the segmentation results

All segmentation results were converted into vector format (ArcView shape file) for the subsequent comparison of geometry. Only eCognition and the Erdas extension ‚Image Segmentation' are able to generate a GIS-readable vector format. All other results were generated in raster format (TIFF) with a unique value for each segment. Geocoding was restored by adding a world file (TFW). Then a raster-to-vector conversion was carried out using Erdas Imagine. Only in the case of the ‚Minimum Entropy Approach' this procedure results to some negative effects, because the implemented triangulation algorithm fractionalises the image without respect to raster boundaries. The preliminary segments are stored in a proprietary vector format, which cannot be saved. Rather the segmentation result was converted into a raster output, which admittedly leads to more partial segments and faulty segmentations (unclosed polygons etc.). These unavoidable effects have a negative influence to the quality assessment.

3.3 Quality assessment

Firstly, all results came under an overall visual survey. General criterions, like the delineation of varying land cover types (e.g. meadow/forest, agriculture/meadow, etc.), the segmentation of linear objects, the occurrence of faulty segmentations and a description of the overall segmentation quality were in the focus of this first step.

Furthermore a detailed comparison based on visual delineated and clearly definable reference areas was carried out. Therefore 20 different areas (varying in location, form, area, texture, contrast, land cover type etc.) were selected and each was visually and geometrically compared with the segmented pendants. The geometrical comparison is a combination of formal factors (area, perimeter, and Shape Index (area-perimeter-ratio)) and the number of segments resp. partial segments (in the case of over-segmentation). For all features the variances to the reference values were calculated.

As partial segments all polygons with at least 50 % area in the reference object were counted. The Shape Index comes from landscape ecology and indicates the polygon form. It is calculated by the quotient of perimeter and four times the square root of area. Additionally the quality of segmentation was visually rated (0 poor, 1 medium, 2 good).

A good segmentation quality is reached, when the overall differences of all criteria between the segmentation results and the associated reference objects are as low as possible. Furthermore the objects of interest should not be over-segmented too much.

4. RESULTS

4.1 Overall visual survey

eCognition: Despite their differences albeit using the same parameters the segmentation the results of eCognition 2.1 (figure 1) and 3.0 (figure 2) are of good quality. Indeed they sometimes contain irregular or ragged delineated segments, especially at seam-forming boundaries and in woody areas. In areas of low contrast the occurrence of faulty segmentations is

possible. Large homogenous image objects are divided arbitrarily sometimes.

eCognition uses a new segmentation algorithm since release 3.0 which enables a result not depending on image size. This is an important improvement because often parameters are tested on small subsets. Nevertheless the old algorithm of version 2.1 could still be used alternatively in the current release 4.0. Altogether eCognition has a high potential due to its multi-scale segmentation and the fuzzy logic based image classification capabilities. Because of the various interfaces to other GIS and remote sensing software systems important user requirements are complied.
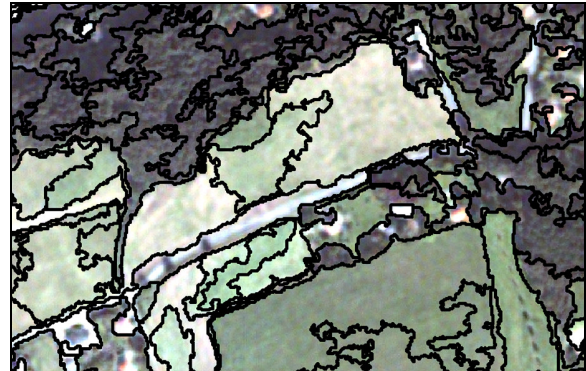

Figure 1. Segmentation result of eCognition 2.1.

Figure 2. Segmentation result of eCognition 3.0.

Data Dissection Tools: The segmentations of the ‚Data Dissection Tools' (figure 3) offer only partly satisfying results. The software tends to a strong over-segmentation of bright image areas, whereby a multitude of small segments occur. Homogeneous areas like fields, meadows or water bodies are segmented almost correct. Only very large areas are divided arbitrarily sometimes. Explicit mistakes of delineation appear in image areas of low contrast (e.g. woody areas). As in bright image areas sometimes single pixels are segmented (comparable to the salt-and-pepper effect). The near infrared was only marginally used in consequence of an unfavourable weighting, which impacts especially the separation of deciduous vs. coniferous forest.
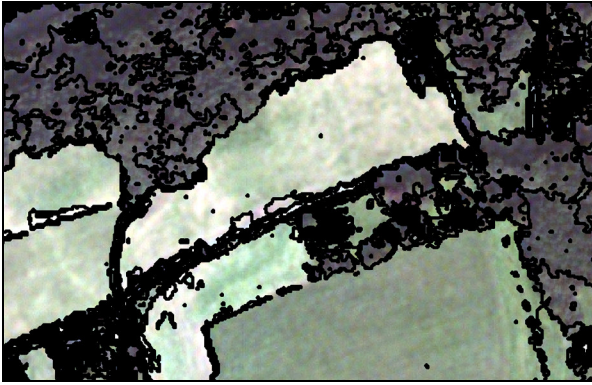
Figure 3. Segmentation result of the 'Data Dissection Tools'.

CEASAR: The program CEASAR 3.1 which was developed for radar data leads to results that cannot be used for further processing (figure 4). The produced segments are compact and of a similar size. This effect occurs even though using different segmentation parameters which yield only to a varying average segment size. Thus, small structures and in particular linear elements are often segmented faulty and an over-segmentation is the consequence. Boundaries of low contrast are represented badly, sometimes boundaries of sufficient contrast too (e.g. forest vs. meadow).
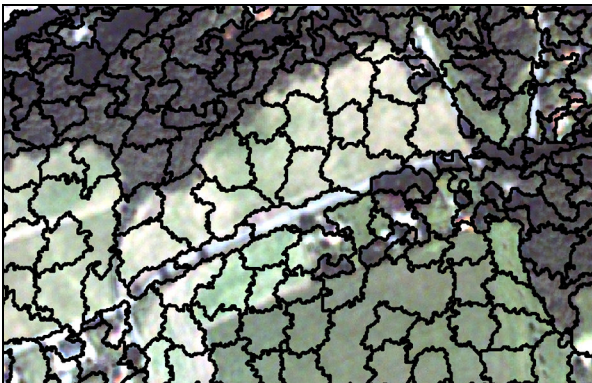

Figure 4. Segmentation result of CAESAR 3.1.

InfoPACK: The result of InfoPACK 1.0 (figure 5), the further development of CAESAR, shows a good delineation for most of the objects, but tends strongly to over-segmentation. Homogeneous areas are thereof less affected and are adequately represented. In particular especially forests and built-up areas were much partitioned. At land cover transitions often interfering seam-forming segments were created. Generally low contrasted boundaries were segmented correctly. Compact and nearly similar sized segments as in CAESAR exist no longer.

For processing scenes of any size the software uses an implemented tiling algorithm. Indeed this leads to additional segment boundaries at the tile transitions. Furthermore margin effects can yield to different results on both sides of the tile boundary. As eCognition the software contains additional classification tools. Thus, a classification based on merging of similar classified and neighbouring segments is possible and this reduces the number of elements to be classified significantly. It must be pointed out, that InfoPACK as well as CEASAR have been developed to analyse very noisy radar data. Hence, the segmentation of optical data could be suboptimal.
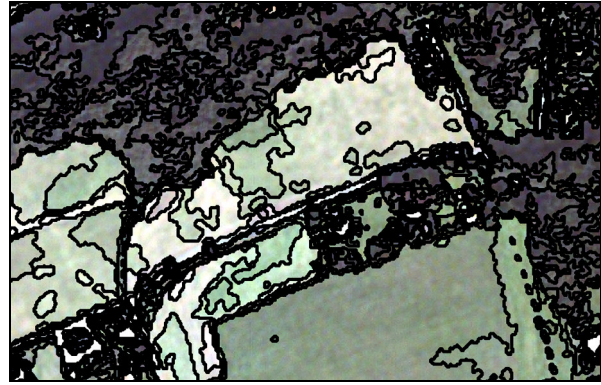

Figure 5. Segmentation result of InfoPACK 1.0.

Erdas Imagine extension 'Image Segmentation': The Erdas Imagine extension 'Image Segmentation' (figure 6) leads to over- and under-segmentation within the same segmentation result. Well-contrasted boundaries between main land cover classes were correctly represented. Areas of low contrast were often not segmented. In particular the delineation of fields vs. meadow was problematic. Forested areas were merged into large conglomerates, with small island segments inside only slightly greater than the parameter minimal segment size chosen. Linear elements were segmented inadequate and homogeneous image objects were divided frequently.

Furthermore, the result contains faulty segmentations in terms of non-explainable horizontal or vertical boundaries. The degree of this effect has been slightly reduced by a new version from September 2002. It was mainly a consequence of the block size used by the software, which can now be set freely in accordance to the available system resources or the image size. Thus, the computing time has been reduced too. But the segmentation quality remained nearly unimproved.
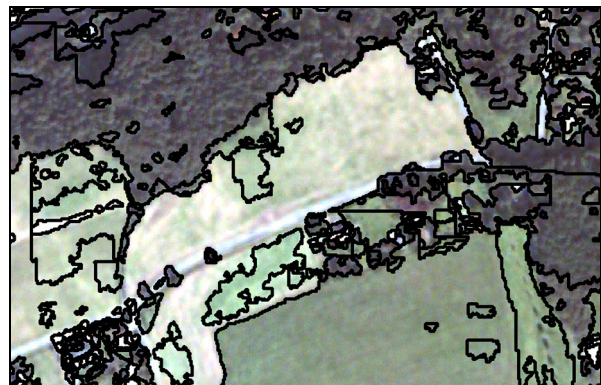

Figure 6. Segmentation result of the Erdas extension 'Image Segmentation'.

'Minimum Entropy Approach': The 'Minimum Entropy Approach' (figure 7) was well reproducing straight boundaries of man-made features (e.g. field boundaries, roads). More complex natural boundaries (e.g. forest edges) were often imprecisely delineated by the used triangulation algorithm. Large homogeneous areas were divided frequently. Simultaneously, effects of the above-mentioned raster-to-vector conversion could be found. Generally it can be pointed out, that the triangulation algorithm often leads to straight segment boundaries or sections

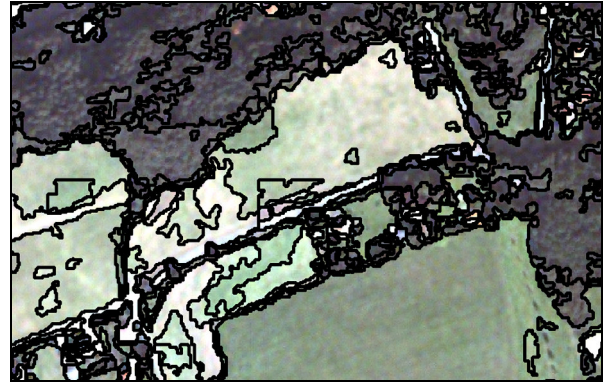Figure 7. Segmentation result of the 'Minimum Entropy Approach'.

Figure 8. Segmentation result of SPRING 4.0.

resp. typical segment shapes which are closer to a human interpretation.

SPRING 4.0: The segmentation results of the region growing algorithm implemented in the image processing software SPRING are showing a good overall impression (figure 8). Homogeneous areas are delineated well but often over-segmented. Heavily textured areas as forests are mostly under-segmented. Sporadic segmentation mistakes occur. However, the ease of operation as well as the data handling of the software is insufficient. The implemented edge-based water-shed-algorithm was also tested, but was leading to worse results (strong over-segmentation) and was therefore not used for his evaluation.

4.2 Comparison based on reference areas

The overall results of all 20 reference areas are cumulated in table 2. As shown in this table the results of SPRING, eCogniton 2.1 and 3.0, InfoPACK and the ‚Minimum Entropy Approach' are reaching the best average area conformity. Except for InfoPACK, the same result is shown in the case of the average conformity of perimeter and the Shape Index. The high conformity of the Shape Index in the case of the ‚Minimum Entropy Aproach' is affected by the segment shapes resulting from the triangulation algorithm which is closer to human interpretation.

Especially within the number of segments both versions of eCognition revealed their strengths. Both led to the slightest over-segmentation in this evaluation. In this regard the results of SPRING could be rated as good. The results of the Erdas Imagine extension ‚Image Segmentation' also reached a slight number of segments, but due to strong differences of the other values the result is indicating under-segmentation.

Segmentation program	eCognition 2.1	eCognition 3.0	Data Dissection Tools	CAESAR 3.1	InfoPACK 1.0	Image Seg-mentation (for Erdas Imagine)	Minimum Entropy Approach	SPRING 4.0
Number of reference areas	20	20	20	10[1]	20	20	11[1]	20
Average difference of area [%]	12,5	15,9	2100,3	75,1	11,1	107,0	13,6	8,2
Average difference of perimeter [%]	15,9	17,2	475,6	35,1	30,9	177,3	10,0	10,8
Average difference of Shape Index [%]	16,7	16,2	38,9	25,5	25,5	87,1	10,0	11,7
Average number of partial segments	1,9	1,8	134,6	10,4	17,1	5,9	9,0	6,2
Average quality, visual evaluated [0…2]	1,0	0,9	0,2	0,0	0,6	0,2	0,8	0,9

[1] differing number due to partial incomplete segmentation results

Table 2.   Cumulated results of all 20 reference areas.

Thus, the results of visual compared qualities results of the individual segmentation programs are reinforced. Only the segmentations by SPRING as well as eCognition 2.1 and 3.0 have reached good overall results. These programs leading to the slightest differences to the reference areas at all factors investigated. Likewise InfoPack and the ‚Minimum Entropy Approach' yielded to an acceptable quality, but InfoPack tends to over-segmentation and the ‚Minimum Entropy Approach' has some processing problems as stated above. The results of the three remaining programs did not reach this quality. They probably failed due to the high complexity of high resolution remote sensing imagery. Often a strong faulty or over-segmentation is the consequence. Furthermore, the grade of conformity with the reference objects is only slight. Indeed it has to be reemphasised, that some of the approaches have not primarily been developed for (optical) remote sensing image analysis.

5. CONCLUSIONS

Due to the dissimilitude of the software implementations the segmentation results are naturally varying. It was shown, that best results have been calculated using the commercial software packages – eCognition and InfoPACK. The only exception is the freeware SPRING, but with the disadvantages of a higher operating expense and a worse handling. However, the use of InfoPACK leads to more over-segmented results. Another algorithm with a high potential is the 'Minimum Entropy Approach to Adaptive Image Polygonization', but there was also an over-segmentation. The results of the other programs were not satisfying user's demands.

Image segmentation has become essential for high resolution remote sensing imagery. The further development of first promising segmentation approaches offers a lot of potentials to make remote sensing image analysis more accurate as well as more efficient. The use of texture information for segmentation could improve the results. Indeed at the moment only InfoPACK provides this option, which was not used for this evaluation. Increasing combinations, for instance with algorithms of feature extraction, edge-oriented or model-based segmentation should be aspired for the improvement of segmentation quality.

Segmentation algorithms respond often very sensitively in the case of negligible variations, like slight parameter chances, the order of segmentation hierarchical approaches or the image data itself (image size, bit depth, etc.). Thus, the user is confronted with a high degree of freedom, which should be minimised. For instance, when selecting parameters by the trial-and-error method the results are highly influenced by subjectivity. The integration of instruments for evaluation of segmentation quality appears desirable.

In future additional segmentation programs will be evaluated, for instance the image processing systems HALCON and IMPACT. Moreover, this more qualitative evaluation will be added by a quantitative comparison using the software SEQ-Tool (Delphi IMM GmbH, 2003). This tool compares the identicalness of polygon outlines (segmented vs. reference).

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