SEGMENTATION OPTIMIZATION FOR AERIAL IMAGES WITH SPATIAL CONSTRAINTS

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ABSTRACT:

Unsupervised segmentation methods are important to extract boundary features from large forest vegetation databases. Finding optimized segmentation algorithms for images with natural vegetation is crucial because of the computational load and the required reproducibility of results. In this paper, we present an approach how to automatically select optimized parameter values for JSEG segmentation. The parameter evaluation is based on a spatial comparison between segmented regions and manually acquired ground truth. City block distance will be used as error metric to define discrepancies between available ground truth and segmentation. Varying the parameter range of values systematically allows to compute corresponding error areas. The smallest error area represents the optimized parameter value.Dependent on the lightness distribution of the selected images and the chosen color quantization, the spatial comparison with the ground truth is limited to local optimization.

1. INTRODUCTION

High resolution images acquired by aircraft or satellites are an important data source for extracting landscape boundaries and other vegetation structures. Large scale landscape and forest inventories depend on reproducible methods for the delineation of distinct vegetation types. Unsupervised segmentation methods represent suitable approaches to extract the required delineation features. Compared to natural images in illustrations and other man-made contexts, remote sensing data for landscape inventories contains often vegetation textures with weak edge structures and faint background.

Swiss National Forest Inventory (NFI) has to record state and changes of the Swiss forest and makes use of a large image database with 7000 aerial images, taken at a scale of 1:30000 with a resolution 0.5m for interpretation and area-based analysis. The image acquisition took place over the last 5 years, therefore varying illumination and inconsistent color distributions for vegetation areas are inherent.

2. SEGMENTATION METHODS

Image segmentation techniques can be classified according to several schemes (Gauch & Hsia, 1992), (Cheng et al., 2001). They distinguish between statistical methods, edge detection techniques, split and merge algorithm, methods based on reflectance models and human color perception. The large number of segmentation publications over the last decades is impressive, but selection of the best method is still a difficult task (Espindola et al., 2006),(Kato et al., 2001). When a suitable method has been evaluated, the segmentation has to be parametrized carefully. The ill-defined nature of the segmentation problem itself does not ease the parameter selection task. Parameter values of segmentation methods consist not only of discrete box-filter dimensions, but also of scaling ranges, e.g. for region growing and color quantization. Therefore evaluation of the optimal segmentation with the corresponding optimal parameter set is far from being a solved problem (Unnikrishnan et al., 2007),(Ndjiki-Nya et al., 2006). To reduce the evaluation complexity and to achieve robuster comparability this paper focus on parameter optimization.

2.1. JSEG

Compared to man-made structures, colors for natural landscape types like forest or agriculture fields contain typically increased luminance and hue variance, mainly caused by fractional fluctuation of surface structures and temporal effects. Due to soft or missing edge structures, local mean values for hue and luminance are fairly similar, therefore segmentation algorithms reveal increased over- and under-segmentation effects (Monteiro & Campilho, 2006). This strongly influences the segmentation results and emphasizes the importance of a systematic and quantitative parameter evaluation.

The unsupervised segmentation algorithm JSEG (Deng & Manjunath, 2001),(Wang et al., 2004) has been selected mainly due to its robust performance for different vegetation images. In this paper we focus on the parameter optimization for JSEG to achieve an automatic delineation of homogenous vegetation areas (Wang & Boesch, 2007).

Systematic parameter evaluation is often limited by time and operational constraints and specially for applications with a broad usage expert values are therefore to be handled with caution. Often expert values are just derived to deliver working results. Empirical values often hamper the tedious search for better settings. But for complex implementations like JSEG, it is also obvious, that no simplified underlying mathematical model like a convolution can be assumed. The peer group filtering of the color quantization, iterative region growing and seed determination of JSEG cannot be reduced to a functional description, therefore according to neural network concepts (Tyukin et al., 2007), optimization of parameter selection remains an approximation problem with infinite randomization of parameter values. The published parameters for JSEG lead to robust results for image collections with homogeneous background (e.g. Berkeley Segmentation Database (Martin et al., 2004)), but forest inventory images are often prone to over-segmentation.

2.2. Evaluation

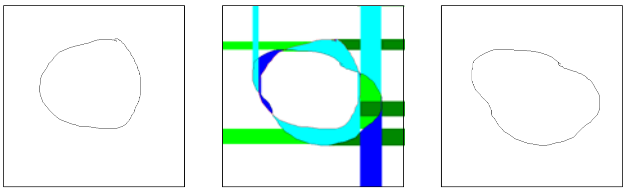
The need for evaluation methods has been published for different vision applications (Unnikrishnan et al., 2007),(Wust et al., 1998),(Jiang et al., 2005),(Zhang & Gerbrands, 1994). Two different approaches exist. On the one hand are dissimilarity measures between segmentation result and ground truth (Borsotti et al., 1998),(Cardoso & Corte-Real, 2005),(Jiang et al., 2006),(Zhang, 1996). On the other hand statistics without *a priori* knowledge are used (Chabrier et al., 2006),(Rosenberger, 2006),(Roman-Roldan et al., 2001), measuring intra- and inter-class disparity and uniformity of the obtained regions. In our application we use the ground truth approach, because the spatial accuracy and topological correctness of visual delineation is still seen as very reliable compared to computed segmentation boundaries.

2.3. Ground truth

Within NFI, manually measured features like the forest boundary line are obtained by stereoscopic interpretation and represent the ground truth. This manual delineation defines the best available forest boundary depending on forest parameters and visual clues and is managed by forest experts. Due to the specific strict rules of the NFI forest definition, the delineation is only available in linear pieces. Therefore result comparison methods which rely on topological comparison of segmentation results cannot be applied (Jiang et al., 2006),(Monteiro & Campilho, 2006). Additional manual interpretation to achieve closed interpretation regions can be done for few examples, but the required effort for the whole NFI image database would be excessive.

3. COMPARISON METHOD

We propose therefore a new optimization method, which is based on spatial constraints between segmentation regions and ground truth using city-block metric as distance criteria (Figure 1).



Groundtruth Difference Segmentation

Figure 1. Difference area in 4 directions (distinct colors for each city block direction)

The area between each segmentation region and the nearest reference line will be calculated in the orthogonal directions +X (West), -X (East), +Y(North) and -Y(South). The 4 areas represent the overall spatial error difference, which needs to be minimized. A single error area can be calculated as follows (n=image columns/lines)

$$\mathrm{diff}(x,y) = \sum |x_i - y_i|,\ i=1..n$$

If there is no segmentation line found between ground truth and image boundary along the city block metric, the nearer image boundary is treated as nearest "hidden" segmentation line (results in rectangle-like shapes as in Figure 1). If there is a real segmentation line, the error area will not reach the image boundary. The concept of "hidden" segmentation line allows to handle over-segmentation as additional error area, otherwise over-segmentations would be ignored. With this metric spatial accuracy and topological correctness can be handled with the same approach.

With systematic variations of the parameter values, the corresponding error areas represent the spatial deviation from the perfect segmentation. This approach allows to optimize parameters in a systematic manner but is also limited to a local neighborhood of the whole parameter space.

The parameter range of values needs to be estimated by experience or well-known values from publications. Expert knowledge and experience is still needed to start with meaningful seed values and ranges.

Despite this limitations, the proposed city block optimization (CBO) is robust enough to select optimized parameter values with a systematic and reproducible approach. Mainly for application targets with limited ground truth data, the presented spatial constraints allow to improve segmentation parameters with a reasonable effort. Due to the high computational burden for advanced segmentation algorithms like JSEG, an exhaustive randomized evaluation of the parameter space is not applicable.

4. EXPERIMENTAL RESULTS

JSEG has two parameters of strong influence on the segmentation results. The first one controls the color quantization window and the other parameter controls the thresholding of the region merging. Because the final region merging has the strongest impact on the delineation of forest areas, we focus on the optimization of threshold parameter *th,* but vary the window size *qw* also.

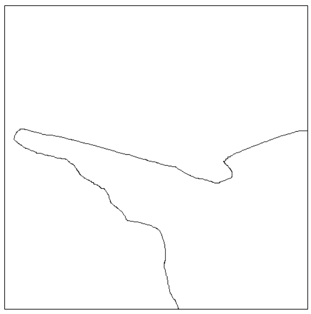


Figure 2. Ground truth "forest cove"

Figures 2-4 and 5-7 show two typical examples for forest boundaries and both images have been processed with a parameter range for threshold *th* from 0.25 until 0.95 (with an increment of 0.05) and quantization windows *qw* ranging from 3x3, 5x5 and 7x7. Figure 2 and 5 show two ground truth images representing a (simplified) manual forest delineation.

Figure 4 shows 5 distinct variations out of 45 processed segmentations for a forest edge in the shape of a cove. The ground truth shows that no gaps are defined as forest boundary delineation. The smallest CBO-value of 26.1 (threshold=0.85) confirms visually the closest correspondence with the ground truth (less color - less error).

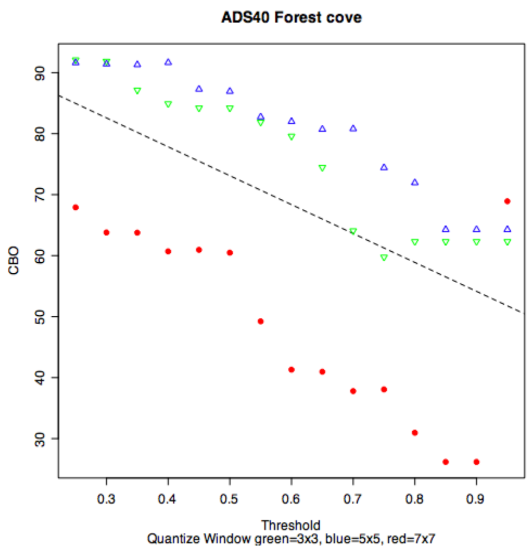
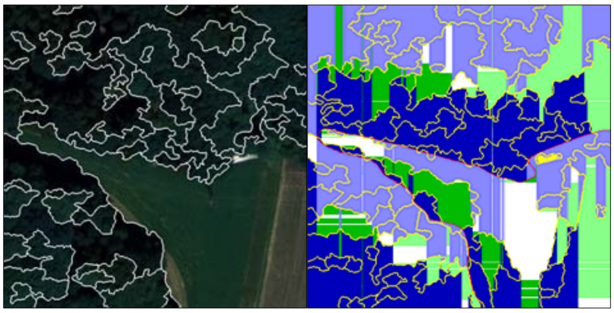
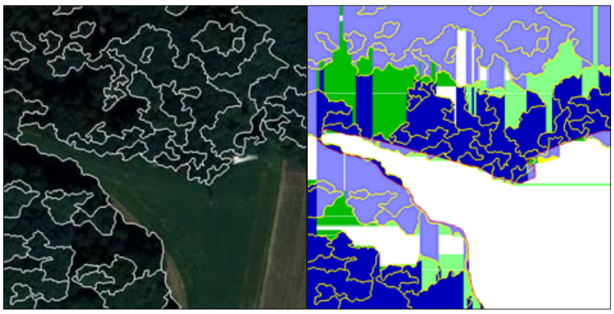


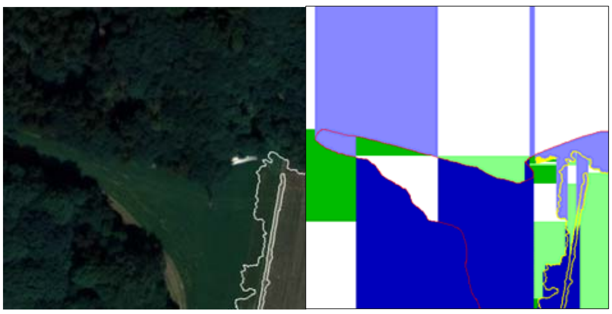
Figure 3. Threshold vs. CBO of "Forest cove"



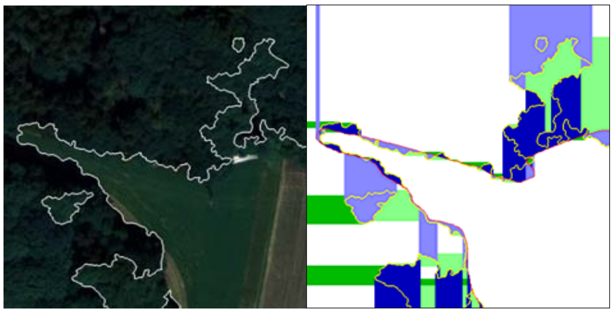
qw=3x3 th=0.25 CBO=92.1



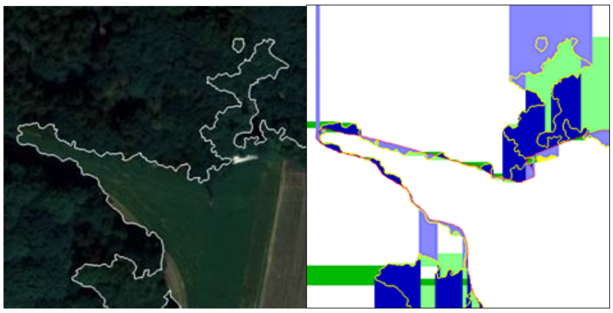
qw=7x7 th=0.25 CBO=67.9



qw=5x5 th=0.85 CBO=64.2



qw=7x7 th=0.80 CBO=30.9



qw=7x7 th=0.85 CBO=26.1

Figure 4. CBO "forest cove"

The evaluation of Figure 3 and 4 reveal the non-linear behaviour of the parameter space for *th*. The regression line for all quantization window sizes shows that higher threshold values yield lower errors, if the window size is 7x7. With smaller window sizes and increasing threshold, the error area is decreasing slower.

The ground truth in Figure 5 contains a typical "straight" forest boundary and additionally one region as a representative gap in the forest cover. The smallest CBO-value of 9.8 (threshold=0.95) from Figure 7 confirms the correct selection by visual comparison. Missing or additional regions within the forest increase the CBO more than the comparatively small differences along the horizontal forest edge. This desired effect corresponds with the fact, that topological errors should be weighted more than boundary differences. Forest edges are often also cluttered with shadow artifacts and therefore the errors caused by under- and over-segmentations lead to more robust CBO-values.

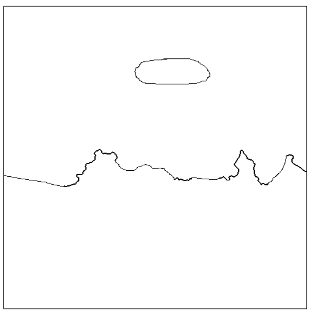


Figure 5. Ground truth "Straight forest edge"

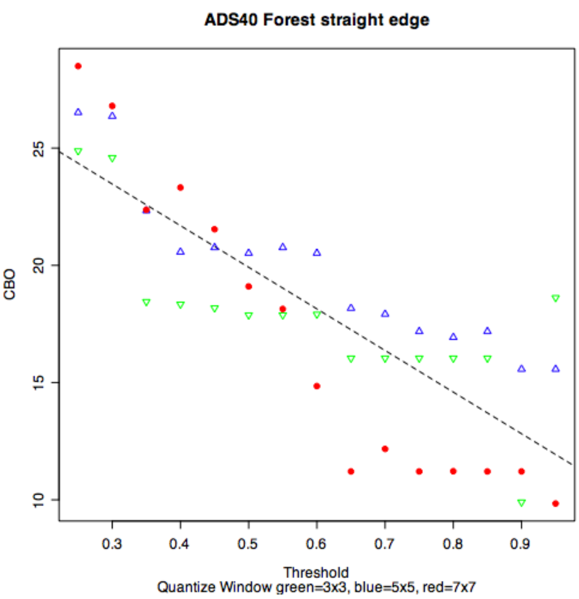
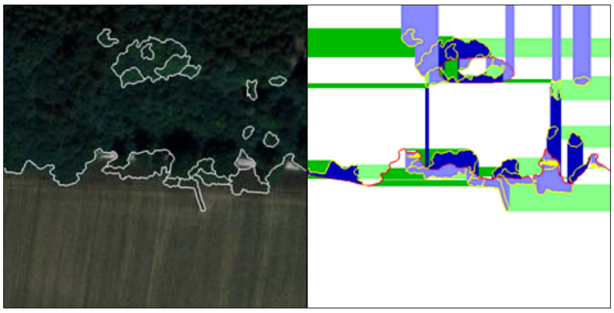
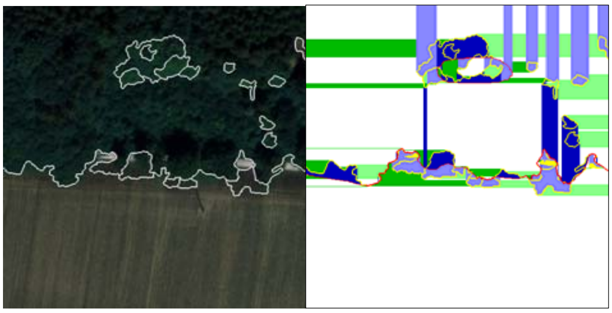


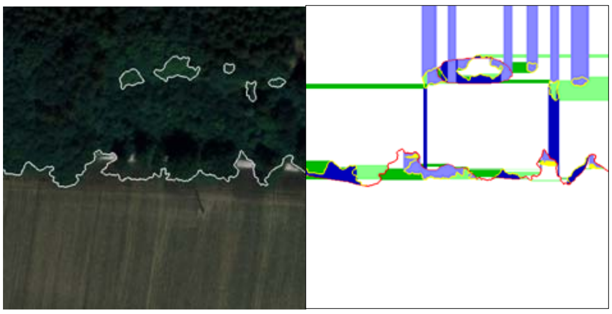
Figure 6. Threshold vs. CBO of "straight forest edge"



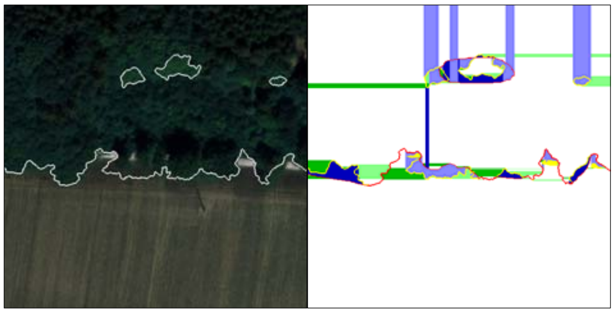
qw=7x7 th=0.25 CBO=28.5



qw=5x5 th=0.25 CBO=26.5



qw=7x7 th=0.60 CBO=14.8



qw=7x7 th=0.65 CBO=11.2

qw=7x7 th=0.95 CBO=9.8

Figure 7. CBO "straight forest edge"

Figure 6 reveals a non-linear characteristic of the error measure CBO=$f(th,qw)$ as in Figure 3, but the regression line for all quantization window sizes shows that higher threshold values yield lower errors for any window size. Nevertheless 7x7 window size seems to be generally closer to the ground truth than smaller sizes.

5. DISCUSSION AND CONCLUSION

Parameter evaluation with the city block optimization (CBO) has its main strengths due to its robustness and when only limited ground truth is available. By using different ground truth examples, CBO allows to optimize segmentation results with a robust and simple metric. The evaluation in the image coordinate space avoids also quantization problems like sliver polygons, which are often encountered as side effect in the result of vectorization algorithms.

The minimum of the CBO values represents the best segmentation compared to the corresponding ground truth. But varying illumination within the NFI image database limits the ground truth comparison to images with a similar lightness distribution. The color quantization of the used JSEG segmentation is very sensitive to strong lightness variations.

The distribution of the parameter values (Figure 3 and 6) can be used to estimate optimized threshold values and to narrow down the initially wide parameter range of values, but it is also evident, that the non-linear function characteristic does not lead to a closed solution. At least a narrowed parameter range of values allows in a further process to search the parameter space with randomized variations (what we initially tried to avoid mainly due to computational time constraints), which should yield an even better optimization result.

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