A MULTISCALAR, MUTICRITERIA APPROACH FOR IMAGE SEGMENTATION

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ABSTRACT:

This work aims at evaluating the relative effect of using different morphological attributes in the segmentation of different images and object classes. An extension to the multi-resolution segmentation algorithm introduced in (Baatz and Shäpe, 2000) that allows several morphological attributes to be considered in the region growing process was implemented. Ten morphological attributes were chosen to compose the heterogeneity criteria, and the quality of spectral-based segmentations was compared with segmentations that combined the original spectral attributes with only one morphological attribute at a time. After that, the impact of using pairs of morphological attributes was also evaluated. Segmentation quality assessment was based on a discrepancy metric called RBSB, proposed in (Feitosa et al., 2006). The experiments were performed over three classes of interest – oil tanks, roofs and trees – present in subsets selected from three pan sharped Quickbird-2 images. The results confirm the importance of including morphological attributes in the segmentation process and raise an interesting discussion for future works.

1. INTRODUCTION

The development of new technologies related to sensor systems and platforms and the consequent increase in the availability of high resolution imagery have exposed the limitations of pixel-based image analysis (Blaschke, 2001) and set the path to a new scientific investigation area called Geographic Object-Based Image Analysis (GEOBIA).

Segmentation is a key process in GEOBIA and its quality is a determining factor for the success of subsequent processing steps, such as recognition and classification.

One of the segmentation algorithms that have produced the better results in the comparative studies performed by Neubert (2006) is the multi-resolution segmentation algorithm available in the eCoginition software suite (Baatz and Shäpe, 2000). It can be regarded as a region growing algorithm that, besides other innovations, considers the values of morphological features in the segmentation process. Despite its commercial success, there are no specific studies that investigate the relative impact in segmentation quality brought by the contemplation of morphological features.

This work aims at evaluating the relative effect of using different morphological attributes in the segmentation of different images and object classes. In this paper we present the results of the analysis of segmentations that employed different morphological features and segmentations carried out using solely spectral-based features.

This paper is organized in the following way. It begins with an overview of the methodology used. Next, a description of the proposed segmentation algorithm is made. Brief descriptions of the optimization method and the segmentation quality assessment method used are then presented. The subsequent sections report the experimental evaluation and main conclusions.

2. METHODOLOGY

An extension to the multi-resolution segmentation algorithm introduced in (Baatz and Shäpe, 2000) was implemented in this work. Such extension allows for several morphological attributes to be considered in the region growing process. In such extension the heterogeneity criterion can be composed by up to ten morphological attributes, including the two present in the original method, namely, compactness and smoothness. The included attributes are: rectangularity, isometry, bulkiness, structure factor, eccentricity, roundness, circular factor and anisometry.

The reference objects were then used in an optimization procedure to automatically find the optimum segmentation parameters for each image and class of objects. Segmentation quality assessment was based on a discrepancy metric called RBSB proposed in (Feitosa et al., 2006). The segmentation parameters subjected to optimization were the scale parameter and the weights of the attributes (spectral and morphological) in the segmentation algorithms heterogeneity criteria.

2.1 Extended Multiresolution Segmentation

This section addresses the image segmentation method proposed in this paper. The method is an extension of the region growing algorithm proposed in (Baatz and Shäpe, 2000).

At the beginning of the segmentation process each image pixel is initialized as a seed, representing an object. After initialization, an iterative process begins. In each iteration, each object is visited only once in a pseudorandom fashion, thus ensuring the distributed growth of objects and reproducibility of results.

When visited, each object identifies which of its neighbouring objects represents the lowest increase of heterogeneity if a fusion is performed. A fusion only occurs if the fusion factor (value of the heterogeneity increase) is lower than the square of the scale parameter s_p, one of the algorithm parameters that acts

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as a global threshold. Segmentation stops when no further merging can be performed.

As shown in Equation 1, the fusion factor has a spectral component h_{color} and a morphological component h_{shape}. The relative importance of each one is given by the shape weight w_{shape}.

$$f = \left(1 - w_{shape}\right) \cdot h_{color} + w_{shape} \cdot h_{shape} \qquad (1)$$

The spectral component of the fusion factor is defined by the object pixels' values, being proportional to the standard deviation of these values, weighted by arbitrary weights defined for each image spectral band. The formulation of the spectral component is given by Equation 2. Obj_1 is the object selected for fusion, Obj_2 is the neighbouring object and Obj_3 is the object resulting from the merging of Obj_1 with Obj_2. In Equation 2, c and w_c are, respectively, the index and weight of the spectral band; σ_c is the standard deviation of the values of the pixels that belong to each object for band c, and n is the number of pixels of each object.

$$h_{color} = \sum_c w_c (n_{Obj3} \cdot \sigma_c^{Obj3} - (n_{Obj1} \cdot \sigma_c^{Obj1} + n_{Obj2} \cdot \sigma_c^{Obj2})) \qquad (2)$$

The morphological component is defined by the relative deviation of the object shape in relation to well-defined geometric shapes. The original algorithm considers two morphological attributes: smoothness and compactness. The method proposed in this paper extends the number of available attributes for the morphological component calculation.

The morphological component formulation h_{shape} is then generalized: not only two, but several attributes can be used. In Equation 3, s and w_s are, respectively, the index and weight of the shape attribute; a_s is the attribute value and n is the number of pixels of each object.

$$h_{shape} = \sum_s w_s (n_{Obj3} \cdot a_s^{Obj3} - (n_{Obj1} \cdot a_s^{Obj1} + n_{Obj2} \cdot a_s^{Obj2})) \qquad (3)$$

2.2 Segmentation Quality

This work used an empirical discrepancy method to assess segmentation quality. Such method quantifies the difference between the segmentation produced by the segmentation algorithm and the reference segmentation (also known as "gold standard" or "ground truth"). A zero discrepancy value represents the maximum or optimum similarity between reference and segmentation. Before a detailed description of the metric, some important concepts (shown in Figure 1) will be defined.

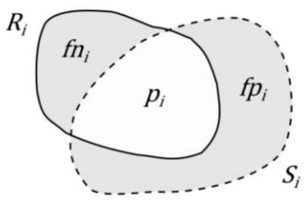


Figure 1: Entities used in the similarity metric.

Let us assume that there are N reference segments delineated by a specialist. Let R_i (i= 1,2, ..., N) be the i-th reference segment. Let S_i be the segment produced by the segmentation algorithm with the largest intercession with R_i. Let us also define:

a) fn_i as the number of pixels of R_i that do not belong to S_i, so called false-negatives;
b) fp_i as the number of pixels of S_i that do not belong to R_i, so called false-positives;
c) $\#()$ as an area operator (in pixels).

The Reference Bounded Segments Booster (RBSB) metric, proposed in (Feitosa et al., 2006), corresponds to the division of the non-intersecting area (false-positives and false-negatives) by the reference area. $F_{RBSB} = 0$ for a perfect match between reference and segmentation and $F_{RBSB} > 0$, otherwise.

$$F_{RBSB} = \frac{1}{N} \sum_{i=1}^{n} \frac{(fn_i + fp_i)}{\#(R_i)} \qquad (4)$$

2.3 Generalized Pattern Search

The optimization method for automatically finding the segmentation parameters was the GPS (Generalized Pattern Search). It belongs to a subset of the direct search methods called *pattern search methods* and was proposed by Torczon (1997) as a generalization of previous methods (Hook and Jeeves, 1961) and the multidirectional search algorithm in (Dennis and Torczon, 1991).

GPS algorithms compute a sequence of solutions that get closer to the global optimum iteratively. At each iteration, the algorithm selects a set of solutions (mesh) around the current solution searching for a solution with a better objective function value than the current one. If that solution is found, the selection (poll) is said successful and the selected solution becomes the current solution in the next iteration. Otherwise, the selection is said unsuccessful and the current solution remains.

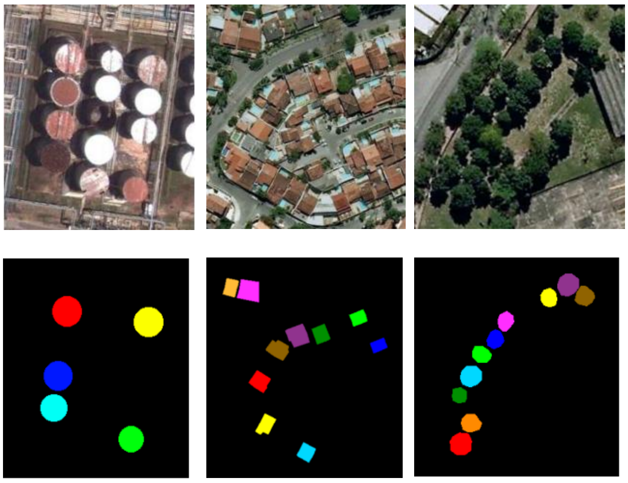
In order to select the solutions to be evaluated, the algorithm adds a set of vectors to the current solution, multiplied by a scale factor, called *mesh size*. In a successful selection, the mesh size is increased; in an unsuccessful one it is decreased. The algorithm stops when the mesh size reaches a minimum threshold.

3. PERFORMANCE EVALUATION

3.1 Input Images

Three subsets were selected from three pan sharped Quickbird-2 images to be used in the experiments. For each image subset, reference objects of a particular class were delineated by a specialist. The target classes selected for the experiments were: oil tanks; roofs; and trees.

Figure 2 (a) shows an image subset of oil tanks from a refinery in Duque de Caxias, Rio de Janeiro. Five reference objects representing oil tanks were delineated. Figure 2 (b) shows an image subset of a residential area in Barra da Tijuca, Rio de Janeiro, with ten reference objects representing house roofs and Figure 2 (c) shows an image subset of the same residential area. Ten reference objects representing isolated trees were also defined. Only the visible spectrum bands (RGB) were used in the experiments.



(a) (b) (c)

Figure 2: Image subsets and reference objects of (a) oil tanks, (b) roofs and (c) trees classes.

3.2 Segmentations Using Only Spectral Attributes

Initially the extended segmentation algorithm was set to use only spectral-based attributes. The scale parameter s_p was estimated for each image/class through the GPS method. The shape weight w_{shape} has been kept equal to 0 and the weights of the bands were fixed equal to 1. Since the GPS method configuration was basically stochastic, for each image 10 experiments were conducted and the minimum values were taken. The obtained parameters values are shown in Table 1.

Reference classes	Scale parameter	Evaluation
Oil tanks	35.84	0.37
Roofs	31.99	0.61
Trees	20.27	0.67

Table 1: Parameters values obtained for spectral-only based segmentations.

3.3 Segmentations using Spectral Attributes and One Morphological Attribute

The goal of the second set of experiments was to compare the spectral-based segmentations with segmentations that combined the original spectral attributes proposed in (Baatz and Shäpe, 2000) with only one morphological attribute at a time. Three parameters were estimated: scale parameter s_p and the shape weight w_{shape}. The weights of the bands were fixed equal to 1. Once again, the segmentation parameters values were obtained for each image/class through the GPS optimization method. Ten experiments were carried out where the minimum (best evaluation) was taken.

The results show (Figure 3) that, for the three images/classes, the evaluations obtained considering one morphological attribute – combined with the spectral attributes – in the heterogeneity criterion were consistently better than the segmentations based only on spectral attributes. Note that the RBSB value for an ideal segmentation is equal to zero.

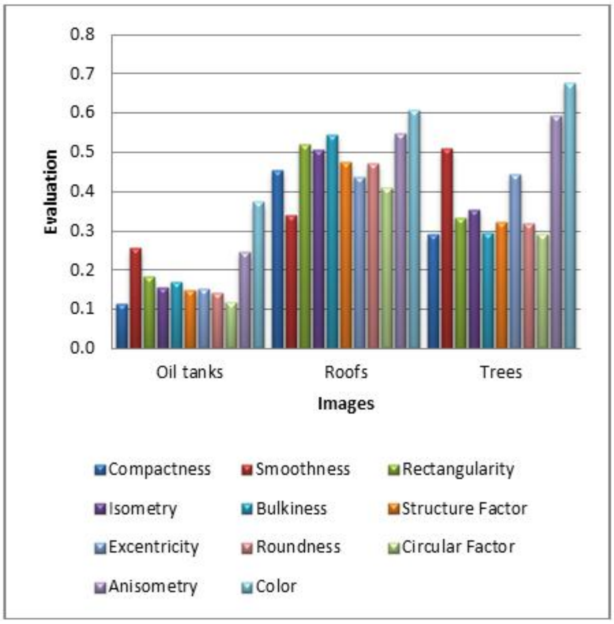


Figure 3: Evaluations (RBSB) of the segmentations using only spectral attributes and using the spectral attributes combined with one morphological attribute.

Figure 4 shows the relative gain brought by the introduction of one morphological attribute in the segmentation algorithm's heterogeneity criteria. The graph shows the relative gain considering the particular morphological attributes responsible for the best segmentation and the best evaluation using only spectral attributes.

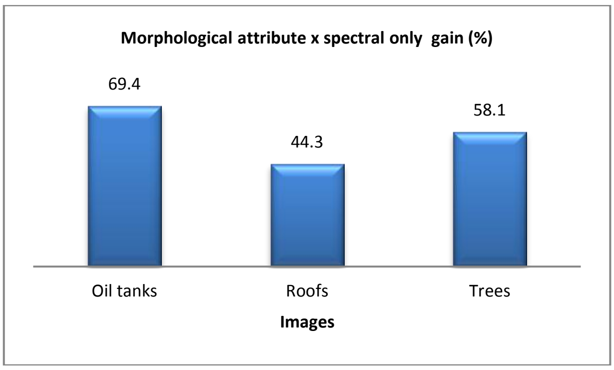
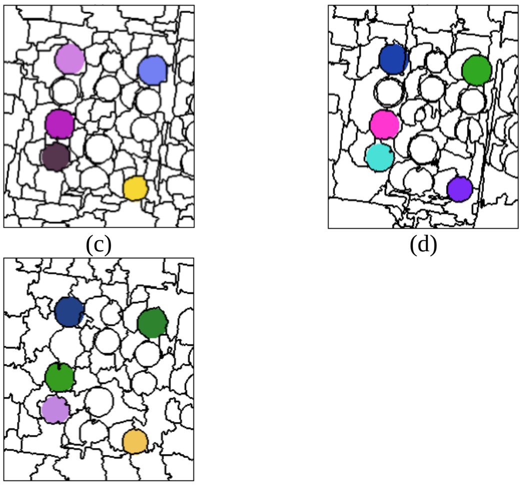


Figure 4: Gain between the minimum of the evaluations of one morphological attribute and spectral-based segmentations.

(a) (b)



(c) (d)

(e)

Figure 5: (a) original image and (b) color-only based segmentation. Images (c), (d) and (e) show the segmentations with the three best-evaluated shape attributes: compactness, circular factor and roundness.

The segmentation images shown in Figure 5 (b)-(e) have as its reference segments the oil tanks present in the original image. The oil tanks have a well-defined circular shape but are spectrally heterogeneous what hinders the segmentation using only spectral attributes.

Figure 5 (a) shows that the segmentation based only on spectral attributes led to oversegmentation and that the resulting segments tried, in general, to delineate the spectral variations. Although the objects outlines are quite well defined the segmentation over the entire image is irregular and branched.

Figure 5 also shows the segmentations yielded by the three shape attributes that led to the best evaluations. The segmentation with the compactness attribute (Figure 5 (c)) produced the best evaluation with a 69.4% gain. This segmentation is significantly better than the previous one as it delineates the given references very well except for the small deviations in the objects outlines.

The segmentations generated by the other 2 attributes got slightly worse evaluations. Although they are still better than the spectral based segmentations they start to present more border irregularities and a little undersegmentation.

3.4 Segmentations using Spectral Attributes and Two Morphological Attributes

The third experiment aimed at verifying if the introduction of another morphological attribute in the heterogeneity criterion could improve the segmentation quality. Three parameters were estimated: scale parameter s_p, shape weight w_{shape} and the shape attribute weight w_s. The weight of the other attribute was calculated as $1 - w_s$ so that the two added up to 1. The weights of the bands were fixed equal to 1. The GPS method was again used and the segmentation algorithm was set to consider two morphological attributes. Again, ten experiments were carried out where the minimum (best evaluation) was taken.

However, scanning all attribute combinations, multiplied by the number of experiments and the number of images made this approach impossible within the available time, since the segmentation is a process computationally expensive. Thus, we chose for a sub-optimal approach, where the attribute that had the best performance in the previous step was fixed, and this attribute was then evaluated with the other attributes in pairs.

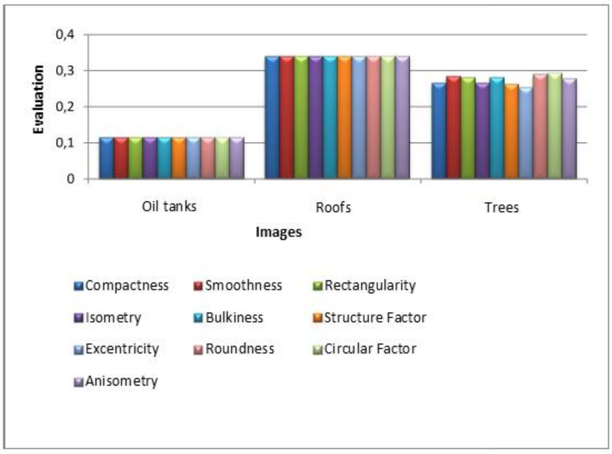


Figure 6: Evaluations of one and two morphological attributes segmentations.

Figure 6 shows that for two images none of the attribute combinations could improve the evaluations obtained with a single morphological attribute. In these cases, the optimization process zeroed the second attribute weight yielding segmentations similar to the ones of the previous experiment. However, for one image the introduction of another attribute has, in fact, led to better segmentation evaluations.

4. CONCLUSIONS

The experiments showed that the quality of segmentations in which morphological attributes were considered was consistently better than segmentations based only in spectral features for all images and object classes considered. These results confirm the importance of including morphological attributes in the segmentation process.

In the experiments conducted on some images, the relative performance of the different morphological attributes was equivalent. However, in most cases, a specific attribute or set of attributes have led to better segmentation evaluations, which indicates that certain morphological attributes can, in fact, be more adequate than others for specific images and target object classes.

The results of the experiments in which two morphological attributes were considered in the heterogeneity criterion were not much conclusive. In part, it comes from the sub-optimal approach used in the investigation. However, the results do point out that the introduction of another morphological attributes can improve the segmentation quality.

It is very likely that there are other attributes that are potentially interesting for the process of image segmentation considering the variety of classes of interest and range of applications. As already stated, the present work already shows, however, important evidence about the utility of shape attributes. In any case, the segmentation program implemented allows for the introduction of any new shape attribute in the composition of the heterogeneity criteria, enabling any future studies on other attributes, images and other target objects classes.

Moreover, it is evident that the results obtained by analyzing the impact of using two or more shape attributes in the segmentation process needs further investigation since the optimization approach used in the related experiments was sub-optimal.

In fact, as the ultimate goal of automatic image analysis is the classification or recognition of object classes, an important unfolding of this work would be to assess the effective contribution of using shape attributes in the segmentation process on the final classification outcome.

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6. REFERENCES

Blaschke, T.; Strobl, J.. What is Wrong with Pixels? Some Recent Developments Interfacing Remote Sensing and GIS. GISZeitschrift für Geoinformationssysteme, 6 (2001), pp. 12-17.

Baatz, M.; Schäpe, A.. Multiresolution Segmentation – An Optimization Approach for High Quality Multi-scale Image Segmentation. In: Strobl/Blaschke/Griesebner (editors): Angewandte Geographische Informationsverarbeitung XII, Wichmann-Verlag, Heidelberg, pp. 12-23, 2000.

Dennis, J. E.; Torczon, V.. Direct Search Methods on Parallel Machines. SIAM J. Optimization, 1 (1991), pp 448-474.

Feitosa, R. Q.; Costa, G. A.; Cazes, T. B.; Feijó, B.. A Genetic Approach for the Automatic Adaptation of Segmentation Parameters. International Conference on Object-based Image Analysis – ISPRS Proceedings, v. 36, n. 4/C42, 2006.

Hooke, R.; Jeeves, T. A.. "Direct Search" Solution of Numerical and Statistical Problems. J. Assoc. Comput. Mach., 8, (1961), pp. 212-229.

Neubert, M.; Herold, H; Meinel, G.. Evaluation of Remote Sensing Image Segmen-tation Quality – Further Results and Concepts. – In: Lang, S.; Blaschke, T. & Schöpfer, E. (Eds.): Proceedings 1st International Conference on Object-based Image Analysis (OBIA 2006), 4.-5. July 2006 Salzburg, International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. XXXVI-4/C42, 6 p., CD-ROM. (ISSN 1682-1777).