A free software tool for Automatic Tuning of Segmentation Parameters

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A free software tool for automatic tuning of segmentation parameters

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Abstract: This paper presents a new free software tool, named Segmentation Parameter Tuning 3 (SPT3), designed for automatic tuning of segmentation parameters based on a number of optimization algorithms using different quality metrics as fitness functions. For a segmentation algorithm to produce segments that correspond in some way to meaningful image objects, its parameters must be properly tuned. Conventionally, it involves a long time consuming series of trials-and-errors. Some initiatives towards designing methods for automatic segmentation parameter tuning rely on a stochastic optimization method. Basically, it searches the parameter space for the values that maximize the level of agreement between a set of reference segments manually delineated by a human operator and the segmentation outcome. Actually, SPT3 is an extension of a previous version, called SPT 2. In relation to the earlier version, SPT3 offers a number of additional features: five segmentation algorithms with computationally efficient implementations (including a parallel GPU based version for two of them), four alternative optimization methods are also included and seven different fitness functions are offered for assess the quality of the segmentation.

Keywords: Geographical Information Science and Systems, Image Processing and Analysis, Open Source technology, Remote Sensing.

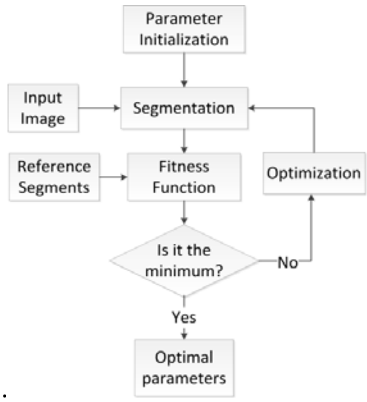
1. Introduction

Segmentation is a fundamental step in GEOBIA since its capability to split the image into discrete meaningful objects affects the whole analysis process. In order to achieve good quality results, segmentation parameters must be properly adjusted. However, this is a complex and time consuming task given that the relation between input parameters and segmentation results is generally unclear.

This work introduces a new free software tool, called Segmentation Parameter Tuning 3 (SPT3), which implements a number of variants of this strategy for Segmentation Parameter Tuning. Although SPT3 can be regarded as an extension of an earlier tool built at the Pontifical Catholic University of Rio de Janeiro for the same purpose (Costa et al., 2008), the SPT3 is an entirely new tool that contains several improvements including a greater amount of segmentation algorithms, optimization methods and fitness functions to assess segmentation quality.

2. SPT2 Overview

SPT3 is an open source software for automatic tuning segmentation parameter values using optimization methods that search for optimum values in their parameter space. Optimality is defined by a fitness function that evaluates the dissimilarity between the segmentation outcome and a set of reference samples. Fig. 1 (a) illustrates how this approach works. The operation of SPT3 is simple and comprises few steps. Initially, the user loads the image selected for segmentation and delineates a set of reference segment samples through the SPT3 graphical user interface (GUI). The segmentation algorithm, the optimization technique and the fitness function are then selected, as seen in Fig. 1 (b), in order to provide, at the end of the process, the adjusted parameter values. The segmented image can also be saved. Besides delivering a recommended set of parameter values, SPT2 may also be used as an independent image segmentation tool. A brief description of the available features is presented in Table 1 and more detailed explanations can be found in the references.

a.


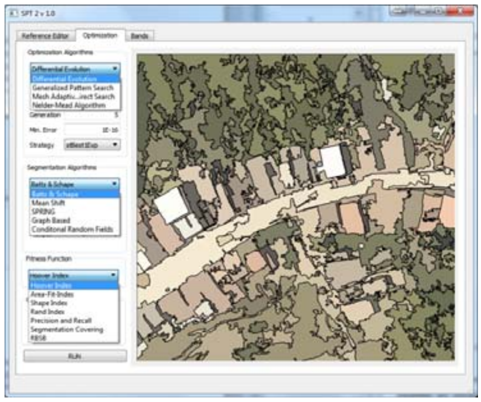
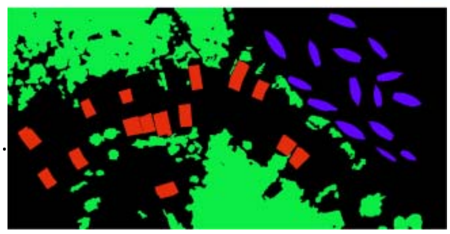
b.


Figure 1. Segmentation Parameter Tuner, a. proposed approach, b. User interface.

3. Experiments and Results

In order to show the functionalities of SPT3, some experiments are reported here using a single image and different configurations, as seen in Figure 2.

(a).


(b).


Segmentation Algorithm	Optimization Method	Fitness Function	Dissimilarity value
CRFb	NM	H	0.7699
Gb	NM	RI	0.0063
MS	DE	RBSB	0.1066
Gb	DE	F	0.00038
B&S	GPS	C	0.1021
MS	GPS	SI	0.00768
B&S	MADS	AFI	0.01595
Gb	MADS	H	0.8977

(c)

Figure 2. a. Image and b. reference samples used in experiments and c. results obtained by SPT3.

The dissimilarity value indicates how unlike the segmentation result is from the reference samples, with a zero value meaning that they are exactly the same. Since there are many

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possible configurations, it is not possible to compare all results. However, it is worth noticing that all generated dissimilarity values are small, meaning good quality segmentation results.

Table 1. Segmentation Parameter Tuner General Specifications.

Segmentation Algorithm	Description
Mean Shift (MS)	Cluster-based approach focused on finding local extrema in the density function of a data set. The center of the search window defined is shifted to the current center of the enclosed data (Comaniciu & Meer, 2002).
Baat & Schape (B&S) / SPRING	Region-growing approaches. Each pixel is taken as an object and they are merged based on different criterions of heterogeneity of the resultant region or Euclidian distances between spectral values (Baatz & Schäpe, 2000, Bin et al., 1996).
Graph-Based Segmentation (GB)	Represents the image as a graph and dissimilarity between pixels as edges. Merges are made between vertices considering that external variation is smaller than internal variations (Felzenszwalb & Huttenlocher, 2004).
Conditional Random Fields (CRFb)	Discriminative probabilistic model. Estimates the conditional probability of a label given certain observation or feature vector from the image (Domke, 2013).
Optimization Techniques	Description
Differential Evolution (DE)	Mainly used to minimize nonlinear and non-differentiable functions in a continuous space of search. The process works iteratively through different generations formed by a set of individuals (potential solutions); at each generation the best suited individuals are kept and are used to generate or better solutions (Storn & Price, 1997).
Generalized Pattern Search (GPS)	Mainly used to solve optimization problems without restrictions and without the need of information about the function derivatives. First, an initial point is defined and a mesh of trial points is created around it with certain directions (patterns). Then, the objective function is evaluated in each one of these points; the point with the lowest value is kept and the mesh size is incremented, otherwise, the actual solution is preserved and the mesh size is reduced (Audet, 2012).
Mesh Adaptive Direct Search (MADS)	Proposed to solve nonlinear optimization problems; it has similar structure than GPS, with the main difference sited in the definition of the search directions, which is not restricted to a finite number of directions, giving the algorithm a bigger set of trial points from where to choose and asses (Audet, 2012).
Nelder-Mead (NM)	Minimize the value of an *n-dimensional* function through the comparison of the objective function values at *(n+1)* vertices in a general simplex, in which the vertex with the highest value is substituted by another one defined by a process of: reflection, expansion, contraction or reduction; then, the new vertex will define the next simplex to be assessed (Nelder & Mead, 1965).
Fitness Functions	Description
Hoover Index (H)	Measures the number of correct detection based on the percentage of overlapping between segmentation and reference (Hoover et al., 1996).
Area-Fit-Index (AFI)	Addresses over-/under-segmentation by analyzing the overlapping area between segmentation and reference (Lucieer, 2004).
Shape Index (SI)	Addresses the shape conformity between segmentation and reference regions (Neubert & Meinel, 2003).
Rand Index (RI)	Measures the ratio between pair of pixels that were correctly classified and the total pairs of pixels (Rand, 1971).
Precision-Recall (F)	Measures the trade-off between Precision and Recall considering segmentation as a classification process (Pont-Tuset & Marques, 2013).
Segmentation Covering (C)	Measures the number of pixels of the intersection of two segments (Pont-Tuset & Marques, 2013).
Ref. Bounded Segments Booster (RBSB)	Measures the ratio between the number of pixels outside the intersection of two segments with the area of the reference (Feitosa et al., 2006).

4. Conclusions

Experiments conducted on SPT3, demonstrated its practicability to find good parameter values for a segmentation algorithm given an input image and a set of reference segments (available at http://www.lvc.ele.puc-rio.br/wp/?p=1403). Moreover, SPT3 can be used as a standalone image segmentation tool. The SPT3 was designed in a modular way, so that future extensions, such as the inclusion of new segmentation algorithms, can be easily incorporated in it.

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