SPT 3.0: A free software for automatic segmentation parameters tuning

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Abstract. This paper presents a free software tool, named Segmentation Parameter Tuner 3 (SPT 3.0), 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, which are delineated manually by a human operator, and the segmentation outcome. This level of agreement is quantified by a metric which compares the segmentation outcome with the reference segments given by the user. As our target is to maximize the level of agreement represent by this metric, it becomes an optimization problem where the metric would be the fitness function. In this version, SPT 3.0 offers many features such as: six segmentation algorithms, which are able to work with Optical, Hyperspectral and/or Synthetic Aperture Data (SAR) images (including parallel GPU-based implementations for two of them), four alternative optimization methods (Differential Evolution, Nelder-Mead, among others) and seven different fitness functions (Hoover Index, Shape Index, among others) are available, which assess the segmentation outcome.

Keywords: image segmentation, parameter tuning, open source, CUDA, hyperspectral imaging, SAR.
Palavras-chave: segmentação de imagens, sintonização de parâmetros, código aberto, CUDA, imagens hiperespectrais, SAR.

1. Introduction

Segmentation is a fundamental step in Geographic Object-Based Image Analysis (GEOBIA) since its capability to split the image into discrete meaningful objects affects the whole analysis process. In order to achieve "good" segmentation results, let's understand good an outcome able to delineate all (or almost all) the objects of our interest in an image; segmentation parameters must be properly adjusted. However, this is a complex and time consuming task due to the unclear and complex relationship between input parameters and segmentation results.

This work focuses on the main changes made to Segmentation Parameter Tuner 3.0 (SPT 3.0), which implements a number of variants for tuning of segmentation parameters. SPT 3.0 was firstly introduced in GEOBIA 2014 (Achanccaray et al., 2014) and many feautures have been additionated henceforth. Currently, Optical and Hyperspectral images are supported.

Furtheremore, a segmentation algorihtm able to work with Optical or SAR images have been added (Jr., 2007) and versions of Region Growing segmentation (Baatz & Schäpe, 2000) and SPRING (Bin et al., 1996), able to work with Hyperspectral images, were included.

The scope of the segmentation algorithms available in the tool is related to the analysis of Optical, Hyperspectral and SAR imagery. The first ones, Optical images, work within the optical spectrum, which extends from approximately 0.3 to $14\mu m$. The second ones, Hyperspectral images, are acquired in many, very narrow, contiguous spectral bands throughout the visible, near-IR, mid-IR and thermal IR portions of the spectrum (Lillesand et al., 2004). Finally, the third ones, SAR images, are obtained using an active sensor in the microwave portion of the electromagnetic spectrum.

Additionaly, two more tabs are available which are focus on execute a segmentation algorithm with a given set of parameters, and to assess the segmentation outcome using a selected metric and a reference given by the user.

The remainder of this paper is organized as follows: In Section 2, the methodology followed by SPT 3.0 in order to find the optimal parameters values of a segmentation algorithm is explained. Then, in Section 3.0, we present the SPT 3.0's Graphic User Interface (GUI), how it works and some results obtained with it. Section 4 concludes the paper and discusses related future works.

2. Methodology

Let's define $p_1, p_2, \dots, p_n$ as a set of parameters belonging to a segmentation algorithm. Then, a metric for segmentation assessment is defined as a quantitatively way to measure how similar a segmentation outcome is with respect to a reference. These kinds of metrics are called *empirical discrepancy methods* according to Zhang (1996). While lower the metric's value is, the segmentation outcome is more similar to the reference. Thus, it is necessary to find the set of parameters values related to the minimum value of this metric, which will be called $\hat{p}$ according to Equation 1.

$$\hat{p} = \underset{p_1, p_2, \dots, p_n}{argmin} \quad metric\big(Seg.Alg.(p_1, p_2, \dots, p_n)\big) \tag{1}$$

Finally, it becomes an optimization problem where the fitness function (or target function) is defined by the metric. The methodology followed to solve this optimization problem is illustrated in Figure 1.

The steps performed by SPT 3.0 are the following. Firstly, the input image is segmented with a set of initialization parameter values. Later, the fitness function is calculated using a reference given by the user. If it is not its minimum value, the optimization algorithm provides a new set of segmentation parameters. This process is repeated iteratively until the minimum value or a convergence criterion is reached (e.g. maximum number of iterations, minimum error, etc.)

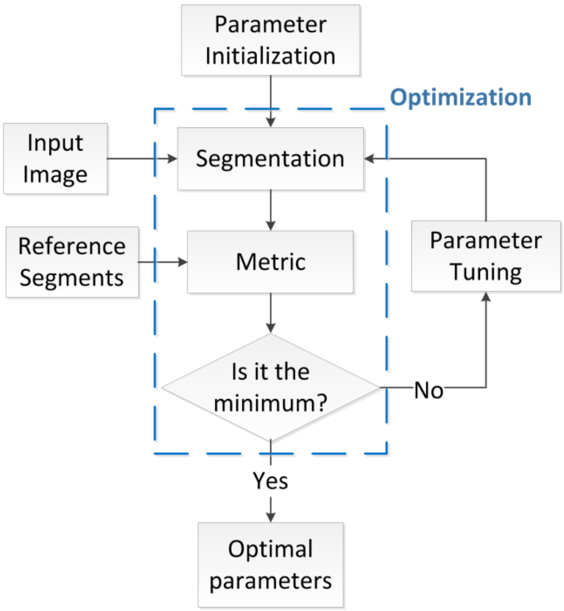

Figure 1. Methodology followed by SPT 3.0.

3. Results

In order to test the functionalities of SPT 3.0, a hyperspectral data set was used. It was collected by the ROSIS optical sensor over the urban area of the University of Pavia, Italy. The image size is 203 × 170, with very high spatial resolution of 1.3 meters per pixel and a number of data channels of 103 (with spectral range from 0.43 to 0.86 μm). Figure 2 shows SPT 3.0's graphic user interface. The experiment performed was done using Nelder-Mead optimization algorithm with Region Growing as segmentation procedure and Precision & Recall as fitness function to be optimized. The segmentation outcome obtained with the optimal parameters found appears on the left, while the reference segments are located on the right. The value of the fitness function is equal to 0.0128516. As it is close to zero, it means that the segmentation outcome is very similar to the given reference.

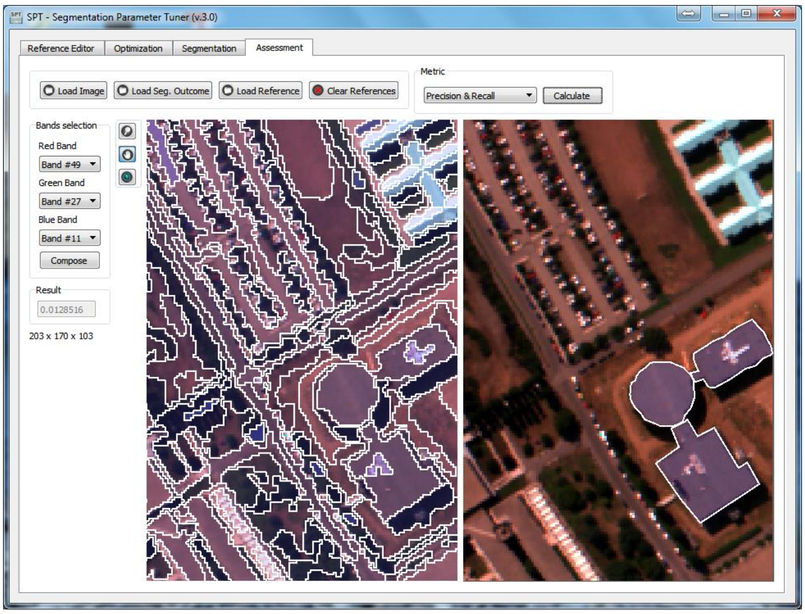

Figure 2. SPT 3.0's graphic user interface for an optimization procedure where the segmentation outcome (left) and reference segments (right) are showed for visual comparison.

The output files generated by each experiment are a report with general information about the experiment, the final segmentation outcome (raster and vector images) related to the optimal values found as well as the minimum value of the fitness function.

4. Conclusions

In this work, Segmentation Parameter Tuner (SPT 3.0) was presented, which is a free tool designed to find optimal parameters of segmentation algorithms based on reference segments given by the user (available at *http://www.lvc.ele.puc-rio.br/wp/?p=1403*). It has many segmentation procedures able to work with Optical, Hyperspectral and/or SAR images. Moreover, SPT 3.0 could be used just to execute segmentation algorithms as well as assess a segmentation outcome. As future work, more segmentation algorithms for Hyperspectral images will be added in addition to the improvement of computational cost of metrics.

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