Spatial Autocorrelation Indicators for Evaluation of Remote Sensing Image Segmentation Algorithms

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1. Abstract

Segmentation algorithms have been often used for extracting information in remote sensing images. Segmentation consists in a process where the pixels of an image are grouped into homogeneous contiguous areas, based on similarity criteria. The resulting image can then be transformed into vector maps by defining spatial objects associated to the contiguous areas.

The performance of segmentation algorithms is strongly dependent on ad-hoc parameters provided by the user. As a consequence, evaluation of segmentation results is a non trivial task, and for that reason it is very important to devise techniques to evaluate the quality of segmentation algorithms and their parameters. A method for evaluating segmentation quality is presented and used to compare image segmentation results. This method considers that a good segmentation has two qualities from a spatial statistics viewpoint: the resulting regions should have internal homogeneity and should be distinguishable from its neighborhood. In such perspective, we propose the use of spatial autocorrelation indicators as a tool for evaluating the quality of segmentation algorithms.

2. Introduction

Methods of image segmentation have become more and more important in the area of remote sensing image analysis. A segmentation process carries out the grouping of neighboring pixels in an image into homogeneous regions based on similarity criteria. Image segmentation tries to divide an image into spatially continuous, disjoint and homogenous regions (Pekkarinen, 2002).

Segmentation algorithms have many advantages over pixel-based image classifiers, since the resulting maps are usually much more visually consistent and more easily interfaced into a geographical information system. Image segmentation is a fundamental element in the integration of imagery into geographical information systems. Errors in the segmentation process may affect the object-based classification accuracy (Soh and Tsatsoulis, 1999). There are a large number of segmentation algorithms for remote sensing images having very different characteristics (Meinel and Neubert, 2002). The two main approaches to segmentation are based on region-growing techniques and edge-based approaches. Extensive experience indicates that region growing techniques are recommended because they exploit spatial information and guarantee the creation of closed regions (Tilton and Lawrence, 2000).

Available segmentation algorithms for remote sensing imagery are based on "ad-hoc" parameters, such as region similarity and minimal area (Bins et al., 1996; Baatz and Schäpe 2000). Therefore, one of the crucial problems when using image segmentation techniques is the selection of adequate parameters to ensure best quality results. This paper addresses this problem, by providing an objective technique of evaluation of image segmentation results based on spatial autocorrelation indexes.

Most earlier works on the issue of evaluation of image segmentation are based on the use of a reference segmentation (produced from visual interpretation) that serves as a comparison basis. These methods include the *discrepancy empirical method* (Zhang, 1996) and evaluation index by Oliveira et al. (2002). In this paper, we propose to evaluate image segmentation results using Moran's *I* global spatial autocorrelation index (Moran, 1950). As described in section 3, our hypothesis is that the spatial autocorrelation index is associated to the choice of parameters that produce the best segmentation result. Before that, we describe the segmentation algorithm used in our assessment in section 2, which is part of the SPRING freeware software developed by our group at INPE. In Section 4, we present a case study that illustrates the potential of our proposal.

3. Description of SPRING's Image Segmentation Algorithm

The segmentation algorithm in the SPRING software (Câmara et al., 1996) is based on a region growing approach. This algorithm is based on two parameters: the *similarity threshold* and the *area threshold.* Two neighboring regions, R_i and R_j, are merged if these conditions are satisfied:

(1) $\textit{threshold condition}: \ dist(R_i,R_j) \leq T$

(2) $\textit{neighborhood condition 1}: \ R_j \in N(R_i) \ \textit{and} \ dist(R_j,R_i) \leq dist(R_k,R_i), \ R_k \in N(R_i)$

(3) $\textit{neighborhood condition 2}: \ R_i \in N(R_j) \ \textit{and} \ dist(R_j,R_i) \leq dist(R_k,R_j), \ R_k \in N(R_j)$

where T is the similarity threshold, $dist(R_i, R_j)$ is the Euclidian distance between the mean gray levels of the regions and $N(R)$ is the set of neighboring regions of region R. After the merging process finishes, regions with an area below a given area threshold are eliminated by merging them with its most similar neighbor (Bins et al., 1996). This algorithm requires the user to select two parameters: the similarity and area threshold. This algorithm has been considered one of the two best options available in remote sensing image software systems on a recent independent survey (Meinel and Neubert, 2004).

4. Segmentation Quality Indicators: Moran's I and Variance

The general idea of our proposal is that a good segmentation has two qualities from a spatial statistics viewpoint: high intra-segment homogeneity and high inter-segment heterogeneity. To assess the inter-segment heterogeneity, we use Moran's *I* autocorrelation index, comparing the average of each segment with the average of its neighbors. Our results indicate that the variation of segmentation parameters is associated with a variation of Moran's *I*. Local minima of this index is associated with good segmentation results. In order to select between local minima of Moran's *I*, we calculate the intra-segment variance. The appropriate choice of parameters is the one that combines a low inter-segment Moran's *I* with a low intra-segment variance.

Spatial autocorrelation is a well-known property of spatial data. This property follows directly from Tobler's (1979) *First Law of Geography*, according to which "everything is related to everything else, but near things are more related than distant things." As a consequence, similar values for a variable will tend to occur in nearby locations, leading to spatial clusters. Moran's I global spatial autocorrelation index indicates the degree of spatial association as reflected in the data set as a whole. The index is shown in Eq. (1) where n represents the total number of polygons, w_{ij} represents a measure of the spatial proximity, y_i represents the observation in polygon i. Each element w_{ij} of spatial proximity matrix W represents a measure of the spatial proximity (spatial contiguity, in this case) of areas A_i and A_j (Bailey and Gatrell, 1995).

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i-\bar{y})(y_j-\bar{y})}{\left(\sum_{i=1}^{n}(y_i-\bar{y})^2\right)\left(\sum_{i\neq j}\sum w_{ij}\right)} \qquad (1)$$

The intra-object variance of the polygon areas was obtained from Eq. (2), where the term v_i represents the variance for the polygon i and a_i represents the area for this same polygon. As we can see, v is a weighted average of the variance, where the weights are the polygon's areas. This approach puts more weight on the larger polygons, whose variance estimative has a smaller variance, avoiding that the instability of the small polygons estimative affects the global v.

$$v = \frac{\sum_{i=1}^{n} a_i \cdot v_i}{\sum_{i=1}^{n} a_i} \qquad (2)$$

5. Results

The experiments described here were based on georeferenced data of ETM+ sensor of the Landsat-7 satellite image (WRS 220/74, August, 14 2001). The study area includes the São Joaquim da Barra municipality in the north of São Paulo state, Brazil. Band 3 (0.63-0.69 μm) of ETM+ was segmented in the SPRING 4.0 software. In this case, a total of 42 segmentations were performed, with different similarity and area thresholds. For the evaluation, we used the average value of each segment, its median and its variance. The results of are the 42 segmentations are shown in Fig. (1), with 7 values of similarity thresholds and 6 values of area thresholds. The patterns demonstrate that there are local minima associated with Moran's I. These local minima correspond to areas where visual assessment indicates a good segmentation result.

For an additional assessment, figure (2a) corresponds to the first line from left to right in the Figure (1). It presents Moran's I for several segmentations in which the area threshold was kept the same (8) and similarity thresholds had values 8, 12, 16, 20, 24, 30 and 50. The two local minima of Moran's I for intra-segment homogeneity assessment occur at values of (8,24) and (8,50). The first combination (8,24) also has a low variance. The results indicate the existence of a possible optimal choice of segmentation parameters at values of area threshold set to 8 and similarity threshold set to 24.

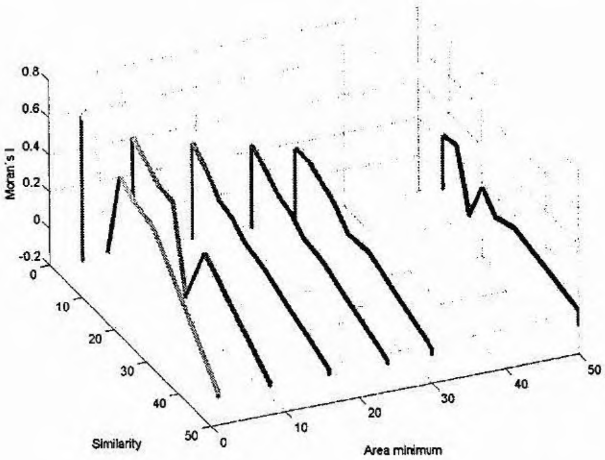
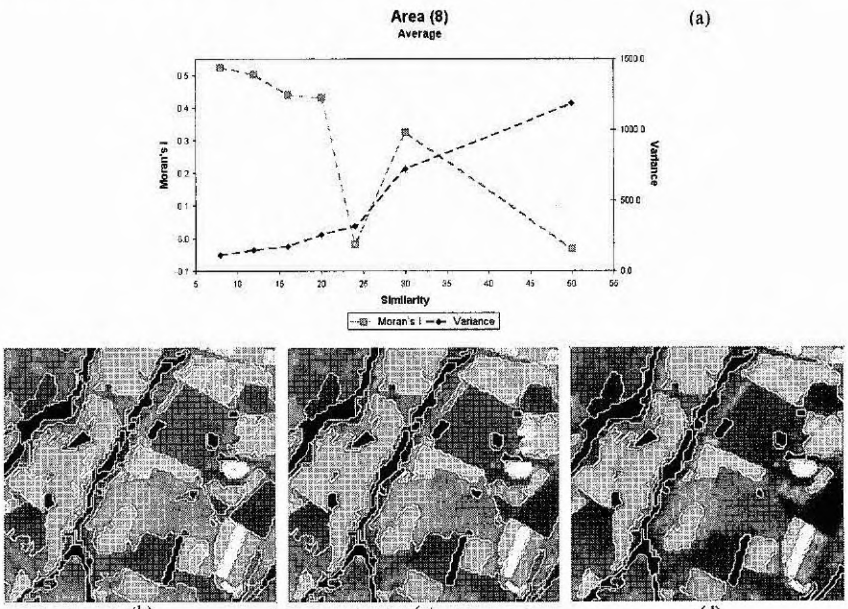


Fig. 1. Moran's I for different combinations of input parameters.

A visual assessment of segmentation results is shown in Figures 2b, 2c, and 2d. Figure 2b shows the visual result for parameters (8,20). Figure 2c shows the result using parameters (8,24), and Figure 2d shows the result using parameters (8,30). In Figure (2b), there are neighboring regions with low contrast, suggesting a super segmentation. In Figure (2d), there are heterogeneous regions with high internal variance, suggesting a sub-segmentation of the image. Therefore, the segmentation with the lowest spatial autocorrelation index is also the one that has the best visual assessment.

(a)



(b) (c) (d)

Fig. 2. Comparison of results with area threshold equal to 8: (a) Moran's *I* and variance values; (b) segmentation results with similarity threshold equal to 20; (c) segmentation results with similarity threshold equal to 24; (d) segmentation results with similarity threshold equal to 30.

6. Discussion

The use of spatial autocorrelation indexes is an objective way of evaluating the performance of segmentation algorithms based on region growing. Our results indicate that low values of spatial autocorrelation are associated to segmentations which produce a pleasing visual result. We consider that our proposed evaluation method has the potential to provide adequate support for users of segmentation algorithms to chose the more appropriate parameters. Future work by the authors includes extending our case studies to a large set of case studies, and also testing the evaluation method with other segmentation algorithms.

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