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"Parameter Selection for Region-Growing Image Segmentation Algorithms using Spatial Autocorrelation"

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Region-growing segmentation algorithms are useful for remote sensing image segmentation. These algorithms need the user to supply control parameters, which control the quality of the resulting segmentation. This letter proposes an objective function for selecting suitable parameters for region-growing algorithms to ensure best quality results. It considers that a segmentation has two desirable properties: each of the resulting segments should be internally homogeneous and should be distinguishable from its neighbourhood. The measure combines a spatial autocorrelation indicator that detects separability between regions and a variance indicator that expresses the overall homogeneity of the regions.

Keywords: Region-growing segmentation, spatial autocorrelation.

2000 Mathematics Classification Index: 62H11 Spatial statistics. 68U10 Image processing. 62H35 Image analysis.

1. Introduction

Methods of image segmentation are important for remote sensing image analysis. Image segmentation tries to divide an image into spatially continuous, disjunctive and homogenous regions (Pekkarinen 2002). Segmentation algorithms have many advantages over pixel-based image classifiers. The resulting maps are usually much more visually consistent and more easily converted into a geographical information system. Among the image segmentation techniques in the literature, region-growing techniques are being widely used for remote sensing applications, since they guarantee creating closed regions (Tilton and Lawrence 2000). Since most region-growing segmentation algorithms for remote sensing imagery need user-supplied parameters, one of the challenges for using these algorithms is selecting suitable parameters to ensure best quality results. This letter addresses this problem, proposing an objective function for measuring the quality of a segmentation. By applying the proposed function to the segmentation results, the user has guidance for selection of parameter values.

The issue of measuring segmentation quality has been addressed in the literature (Zhang, 1996). For closed regions, Liu and Yang (1994) propose a function that considers the number of regions in the segmented image, the number of the pixels in each region and the colour error of each region. Similarly, Levine and Nazif (1985) use a function that combines measures of region uniformity and region contrast. None of these proposals makes direct use of spatial autocorrelation. Spatial autocorrelation is an inherent feature of remote sensing data (Wulder and Boots, 1998) and it is a reliable indicator of statistical separability between spatial objects (Fotheringham et al., 2000). Using spatial autocorrelation for measurement of image segmentation quality is particularly suited for region-growing algorithms, which produce closed regions.

The proposed objective function considers that a segmentation has two desirable properties: each of the resulting segments should be internally homogeneous and should be distinguishable from its neighbourhood. The function combines a spatial autocorrelation index, which detects separability between regions, with a variance indicator, which expresses the overall homogeneity of the regions. The main advantage of the proposed method is its robustness, since it uses established statistical methods (spatial autocorrelation and variance).

2. A typical region-growing image segmentation algorithm

The assessment of the proposed objective function used the region-growing segmentation used in the SPRING software (Bins, Fonseca et al. 1996). As a recent survey shows (Meinel and Neubert 2004), this algorithm is representative of the current generation of segmentation techniques and it ranked second in quality out of the seven algorithms surveyed by the authors. This algorithm uses two parameters: a *similarity threshold* and an *area threshold*. It starts by comparing neighbouring pixels and merging them into regions if they are similar. The algorithm then tries iteratively to merge the resulting regions. Two neighbouring regions, R_i and R_j, are merged if they satisfy the following conditions:

(1) Threshold Condition: $dist(R_i, R_j) \leq T$

(2) Neighbourhood Condition 1: $R_j \in N(R_i)$ and $dist(R_j, R_i) \leq dist(R_k, R_i)$, $R_k \in N(R_i)$

(3) Neighbourhood Condition 2: $R_i \in N(R_j)$ and $dist(R_j, R_j) \leq dist(R_k, R_j)$, $R_k \in N(R_j)$

In the above, T is the chosen *similarity threshold*, $dist(R_i, R_j)$ is the Euclidian distance between the mean grey levels of the regions and $N(R)$ is the set of neighbouring regions of region R. Also, regions smaller than the chosen *area threshold* are removed by merging them with its most similar neighbour (Bins, Fonseca et al. 1996). The results of the segmentation algorithm are sensitive to the choice of similarity and area thresholds. Low values of area threshold result in excessive partitioning, producing a confusing visual picture of the regions. High values of similarity threshold force the union of spectrally distinct regions, resulting in undersegmentation. In addition, the right thresholds vary depending on the spectral range of the image.

The need for user-supplied control parameters, as required by SPRING, is typical of region-growing algorithms (Meinel and Neubert 2004). For example, the segmentation algorithm used in the e-Cognition® software (Baatz and Schape 2000) needs similar parameters: scale and shape factors, compactness and smoothness criterion. Therefore, the objective function is useful for region-growing algorithms in general.

3. An indicator of segmentation quality

Given the sensitivity of region-growing segmentation algorithms to user-supplied parameters, this letter proposes an objective function for measurement of the quality of the resulting segmentation. The function aims at maximizing intrasegment homogeneity and intersegment heterogeneity. It has two components: a measure of intrasegment homogeneity and one of intersegment heterogeneity. The first component is the intrasegment variance of the regions produced by a segmentation algorithm. It is calculated by the formula:

$$v = \frac{\sum_{i=1}^{n} a_i \cdot v_i}{\sum_{i=1}^{n} a_i} \tag{1}$$

In equation (1), v_i is the variance and a_i is the area of region i. The intrasegment variance v is a weighted average, where the weights are the areas of each region. This approach puts more weight on the larger regions, avoiding possible instabilities caused by smaller regions.

To assess the intersegment heterogeneity, the function uses Moran's I autocorrelation index (Fotheringham et al., 2000), which measures the degree of spatial association as reflected in the data set as a whole. Spatial autocorrelation is a well-known property of spatial data. Similar values for a variable will occur in nearby locations, leading to spatial clusters. The algorithm for computing Moran's I index (the spatial autocorrelation of a segmentation) uses the fact that region-growing algorithms generate closed regions. For each region, the algorithm calculates its mean grey value and determines all adjacent regions. In this case, Moran's I is expressed as:

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

In equation (2), n is the total number of regions, w_{ij} is a measure of the spatial proximity, y_i is the mean grey value of region R_i, and $\bar{y}$ is the mean grey value of the image. Each weight w_{ij} is a measure of the spatial adjacency of regions R_i and R_j. If regions R_i and R_j are adjacent, w_{ij} is one. Otherwise, it is zero. Thus, Moran's I applied to segmented images will capture how, in average, the mean values of each region differ from the mean values of its neighbours. Small values of Moran's I indicate low spatial autocorrelation. In this case, the neighbouring regions are statistically different. Local minima of this index signal locations of large intersegment heterogeneity. Such minima are associated to segmentation results that show clear boundaries between regions.

The proper choice of parameters is the one that combines a low intersegment Moran's I index (adjacent regions are dissimilar) with a low intrasegment variance (each region is homogenous). The proposed objective function combines the variance measure and the autocorrelation measure in an objective function given by:

$$F(v, I) = F(v) + F(I) \tag{3}$$

Functions $F(v)$ and $F(I)$ are normalization functions, given by:

$$F(x) = \frac{X_{\max} - X}{X_{\max} - X_{\min}} \tag{4}$$

4. Results and discussion

To assess the validity of the proposed measure, we conducted two experiments. The first experiment used a 100x100 pixel image of band 3 (0.63-0.69 µm) of the LANDSAT-7/ETM+ sensor (WRS 220/74, 14 August 2001). We created 2500 segmentations, with similarity and area thresholds ranging from one to 50. The values of the objective function are shown in figure 1a and the image is shown in Figure 1b. The maximum value occurs for an area threshold of 22 and a similarity threshold of 25. This maximum value matches the visual interpretation of the result, which achieves a balance between undersegmentation and oversegmentation.

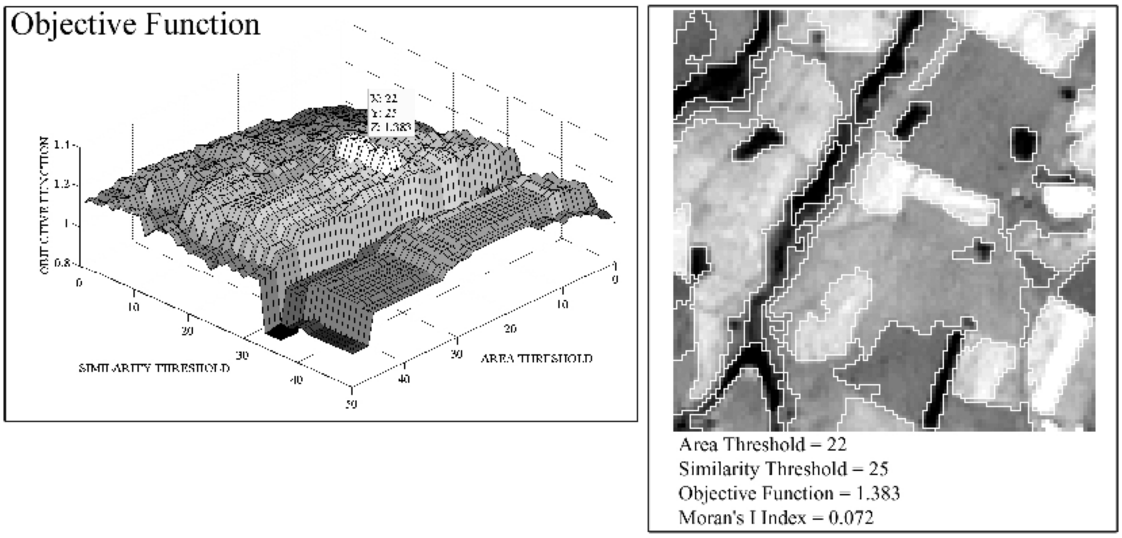
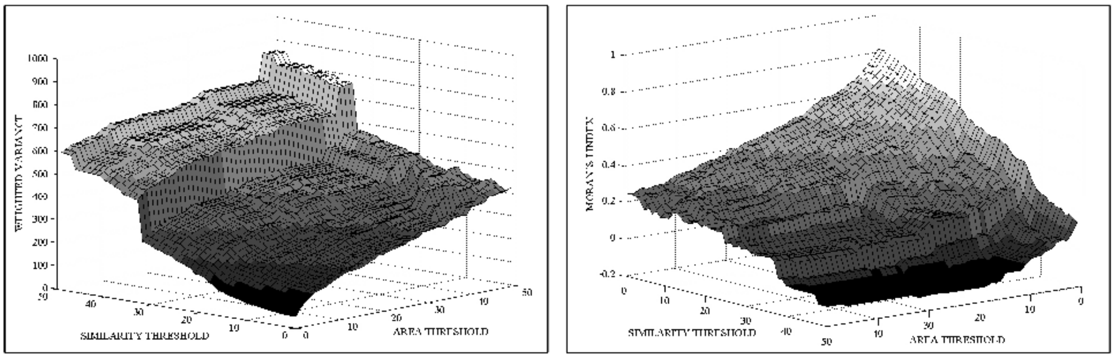


Figure 1. Left: the objective function for test image, whose maximum value occurs when the similarity threshold is 25 and area threshold is 22. Right: Resulting segmented image.

The weighted variance for the 2500 segmentations is shown in figure 2a. Small values of similarity and area thresholds produce few regions and the weighted variance will have small values. The weighted variance increases with the similarity and area thresholds. The values of Moran' I are shown in figure 2b, which indicates the local minima. These local minima are cases where each region is internally homogenous and is dissimilar from its neighbours.



(a) Weighted Variance (b) Moran's I Index

Figure 2. Left: weighted variance for 2500 segmentations of test image. Right: Moran's I for 2500 segmentations for test image.

Figure 3 shows how Moran's I index varies, given a fixed area threshold of 22 and a similarity threshold ranging from one to 50. Visual comparison of three results (with similarities of 19, 29, and 36) shows the segmentation with smallest value of Moran's I matches a more visually pleasing segmentation result.

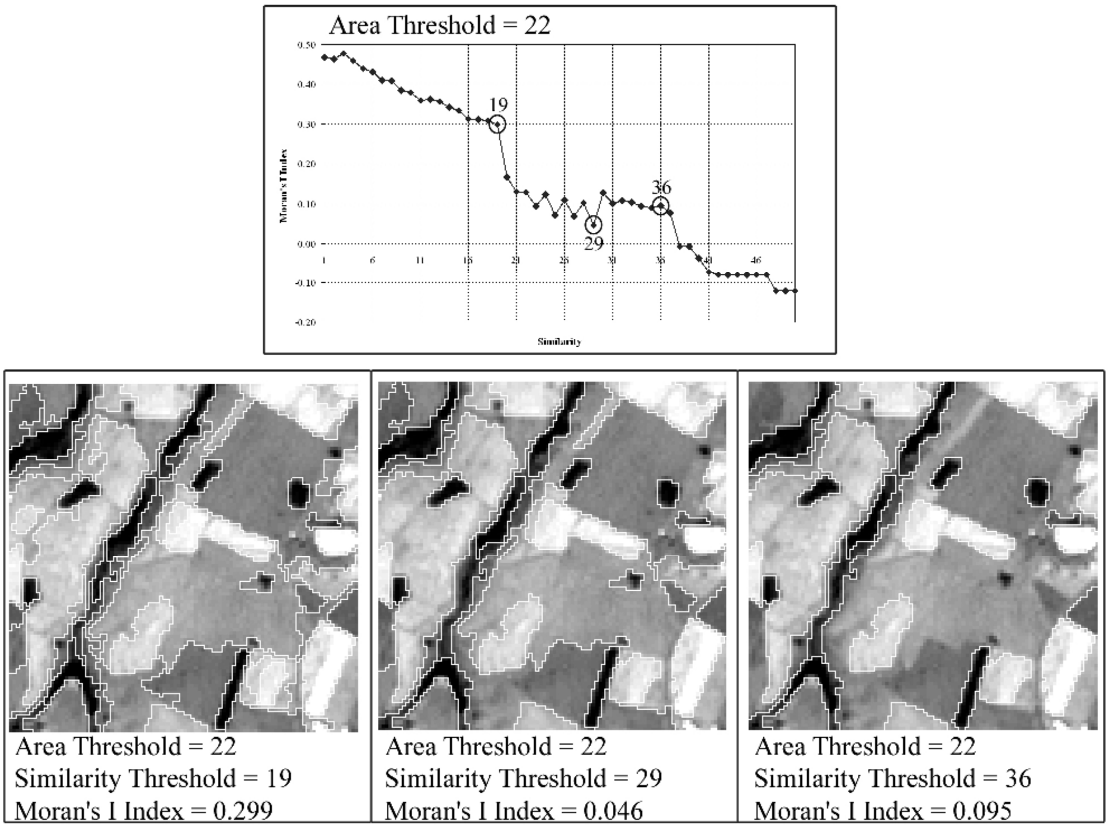


Figure 3. Top: values of Moran's I for a fixed area threshold (22) and a similarity value ranging from 1 to 50. Bottom (left to right): Segmentations with different similarity thresholds (19, 29 and 36).

The second experiment used a synthesized image of 426x426 pixels, as suggested by Liu and Yang (1994). Figure 4 shows and the variation of its objective function. The maximum value of the objective function matches visual interpretation of the results. The best segmentation has a high homogeneity of the segments, and a clear distinction between neighbouring segments.

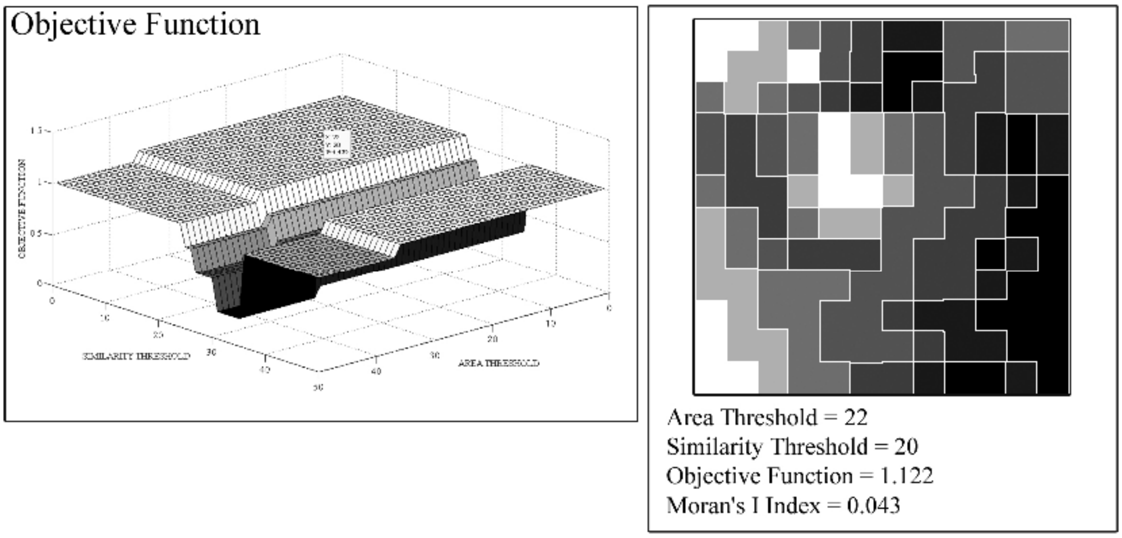


Figure 4. Left: objective function for synthesized image. Right: Best segmentation (similarity parameter is 20 and area parameter is 22).

5. Conclusion

The emerging use of region-growing segmentation algorithms for remote sensing imagery requires methods for guiding users as to the proper application of these techniques. This letter proposes an objective function that uses inherent properties of remote sensing data (spatial autocorrelation and variance) to support the selection of parameters for these algorithms. The proposed method allows users to benefit from the potential of region-growing methods for extracting information from remote sensing data.

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