Merging regions based on the VDM distance

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In a per-object classification system, many authors have advised a two-step process: First by obtaining small, homegeneous objects, second by merging those regions. In this paper, we present a new method to decide whether two regions belong to the same class or not.

An extension of Chang and Li's method of adaptive region-growing is proposed, in order to take into account the case of multiband images. Region dispersion is calculated by means of the Vector Degree of Match (VDM) distance, proposed by Baraldi and Parmiggiani. This distance measures the similarity degree of two n-dimensional vectors. Each intra-region similarity is computed and then compared with other regions. Instead of defining a similarity degree fixed threshold, obtained by a trial and error process, we propose an adaptive one, based on a global percentage similarity.

In short, this work proposes a reduction of the features space into a one-dimensional space which measures the similarity by a non-parametric criterion, thereby avoiding the determination of the density function problem.

INTRODUCTION

One of the most critical activities of Remote Sensing consists in the classification process. This can be accomplished by using the pixel or the homogeneous object as the basic element to be classified. The advantages of homogeneous objects over per-pixel classification are already well-known to the scientific community. The extraction and classification of homogeneous objects approach arose as a solution to the “salt and pepper” problem [1]. However it also offers a solution to several problems in the per-pixel classification methods. As a first step, it identifies those areas (homogeneous objects) with the “same” general cover type, where the term “same” refers to the criteria used to establish the similarity between pixels. In the second and final step, the extracted homogeneous objects are classified in such a way that all pixels belonging to a same object are labeled in a single classification decision.

These algorithms have to decide by some means whether two pixels or two regions belong to the same class. Region-growing techniques are widely used for this purpose. Nevertheless, the classification result is very sensitive to the parameters of the algorithms. Thus, permissive parameters entail merging between distinguishable adjacent regions. On the other hand, strict parameters involve oversegmentation.

In this paper, an adaptive region growing algorithm is proposed. Furthermore, the VDM distance [2] is used to decide if two regions belong to the same class.

In the following sections, the background and outline of the algorithm are described. The next section shows the results obtained over a small multispectral Landsat TM image. In the last section, the conclusions reached are discussed.

METHODOLOGY

The first step

In low-level vision, the fact that cooperation between two techniques for segmentation produces much better results than by either technique alone has already been demostrated. In particular, a survey of region growing and edge detection integration can be found in [3] whilst a survey to the multispectral case is shown in [4].

Region-based methods focus on finding parts of images which are homogeneous for a given set of properties. These techniques can be used in both a supervised and unsupervised way. At the same time, they allow for a wide set of segmentation parameters: statistical texture parameters, fractal measurements, similarity, etc.

In our work, we used ISODATA algorithm in order to obtain a first segmentation of the image. The output of this step is an image composed of several regions. Many authors advise obtaining an oversegmented image in the first step, and then improving the result by merging homogeneous regions afterwards.

The second step

The simplest technique to measure two region similarity is by comparing its centroids. The problem is therefore reduced to merging those regions whose similarity is greater than a given threshold. This technique has a serious drawback: it is

inadequate when the shape of the region in the feature space is the discriminating element .

When two regions are to be merged, several choices arise, depending on spatial relationship, size of the regions, number of similar regions found, etc. The moment of updating the system to take into account the new region is another sensitive point, since the results of the algorithm may depend on the order of the comparisons. After merging the regions, features of the new region have to be computed. Therefore, in order to obtain an ideal algorithm, only that region in the neighborhood with the highest similarity to the region of interest should be merged . The computational cost of this option is clearly higher than the compare-merge-compare-merge approach. Despite this, we preferred this option.

The basic element in this second step is an extension to the multidimensional space of the Adaptive Homogeneity Test (AHT) shown in [5]. Among the advantages of this algorithm is the dynamic and automatic computation of the thresholds of acceptance in the merging process. The algorithm works directly with the histograms of the regions and it does not assume any kind of distribution in the data (using a non-parametric criteria). AHT allows us to define a non supervised system governed only by a parameter λ ($0 \leq \lambda \leq 1$), which defines the central portion of the region feature values that define the acceptance area. Given a number of regions composed of *n* primitive regions with feature values $\{X_{i1},\ldots X_{in}\}$, and given a λ for each region R_i in the image, the region's adaptive range (l_{i1},l_{i2}) is defined by (1).

$$\Pr(li1 < Xj < li2) = l$$
$$\text{and } \Pr(li2 \leq Xj) = \Pr(Xj \leq li1) = \frac{1-l}{2} \qquad (1)$$

For two regions to be considered homogeneous, each region's feature mean has to fall within the other region's adaptive range. Chang and Li [5] found that $\lambda \in (0.8,0.85)$ produced satisfactory results.

If the origin of the histogram is moved to the region's mean feature value in the one-dimensional case, this new histogram could be seen as the representation of the difference between the pixels and the centroid of a region. This change allows us to introduce the *distance* concept. There exist many distance functions, among them Minkowsky, Mahalanobis, Chebychev, quadratic, correlation, etc. In a number of them, an uncorrelated coordinate system and/or a known probability function (usually Gaussian) is assumed. Both premises fail in remote sensing images [6]. Therefore, non-parametric distance functions as VDM are required.

Conceptually, the pixels of a region can be seen as a cluster in the feature space. Generalizing the criterion shown in [5], the latter checks whether the centroids of both regions fall within the interior of eachother's region, in a dynamic distance related to λ_k in each dimension. The representation of this threshold distance in the feature space is a parallelepiped. Mahalanobis distance is similar, but it considers a spheroid as the acceptance area, assuming a Gaussian distribution.

Depicting the distance between the pixels of the region to its centroid results in a histogram that will tend to be grouped near the origin in those homogeneous regions, but will be sparse in high variance regions. This projection into a one-dimensional space involves λ parameter being considered as the fraction of elements in a region that are nearer to its centroid, as can be seen in Fig.1. The similarity computation is reduced in order to check whether the distance between the centroids of both regions is included in both acceptance regions. A solution similar to Chang and Li's [5] is adopted to take into account the number of pixels in each region, so that when two small regions are compared, only a maximum distance is checked, and if one small region is compared with a large one, only the centroid of the small region is tested to see if it falls within the large region area of acceptance. An overview of the process can be seen in Fig. 5.

Improvements

VDM distance has two problems: first, it weighs each band equally, independently of its variance. On the other hand, it involves a high computational cost, because it has to compute again the similarity levels after each merging. In order to reduce the impact on the final results of some bands, a normalization to the highest variance band is carried out. The problem of high computational cost can be dealt with a statistical approach. Thus, instead of considering all the pixels in a region in order to calculate its similarity histogram, only a subset of them is computed. In order to perform this sampling, a representative number of pixels in the region has to be computed. Ideally, this number should be calculated from the variance of the region, although the computational cost is not thereby reduced. A less expensive alternative would be to calculate the number in question from the size of the region.

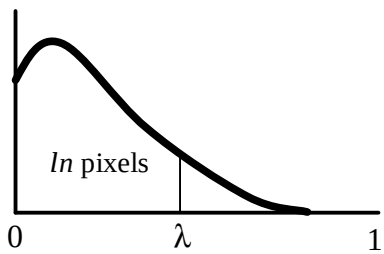

Figure 1. Area of acceptance in a one-dimensional space.

RESULTS

In Fig. 2, the image used in our test can be seen. We fed our algorithm with two initial segmentations: one strict and the other one less restrictive. Both of them can be seen in Fig. 3. Finally, the classified image can be seen in Fig. 4.

CONCLUSIONS AND FUTURE WORK

In this paper, we have presented an algorithm that allows us to refine a preliminary segmentation of a multispectral image by a region-merging method. This method is based on a similarity criterion defined by a non-parametric distance function. The only parameter required by the algorithm is λ, a global percentage that defines the acceptance area of each region and makes the algorithm more adaptible. Furthermore, some speed and accuracy improvements have been proposed.

Further development has to be carried out in order to prove the suitability of the algorithm in other types of multispectral images as well as to bring about a parallelization of the algorithm, with the purpose of reducing the duration of the classification process.

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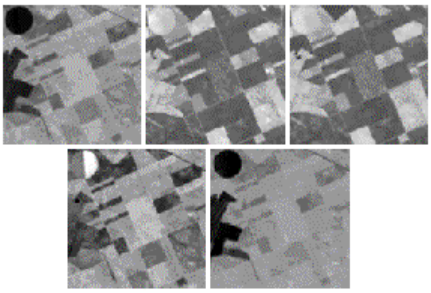

Figure 2. 5 band Landsat TM 5 image

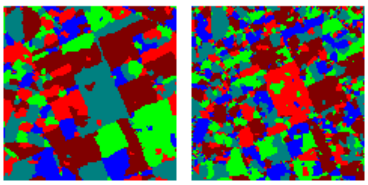

Figure 3. Initial segmentation

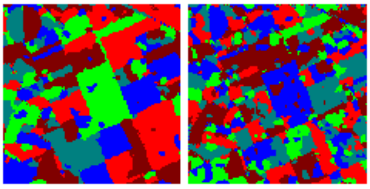

Figure 4. Final classification

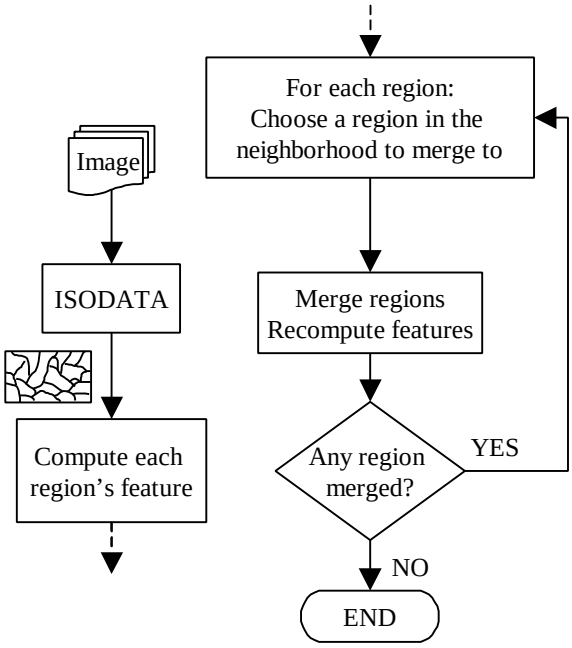

Figure 5. Schema of the algorithm