A STATISTICAL APPROACH FOR SIMULTANEOUS SEGMENTATION AND CLASSIFICATION

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ABSTRACT

This paper presents an alternative object based classification for multispectral remote sensing images. Instead of classifying the images after the segmentation process, it is suggested to involve some steps of objects recognition during the segmentation process in order to improve the final classification results. The methodology is based on the statistical distribution of object classes. Experiments were performed with a TM-Landsat image and the results were compared with a reference data. The results indicate the soundness of the proposed methodology.

***Index Terms*—** object based classification, pattern recognition, statistical distribution

1. INTRODUCTION

With the increased availability of high spatial resolution remote sensing images, many techniques have been proposed aimed to exploit not only the radiometric features, but also the texture and morphology information of targets present in the image data [1]. These techniques are recognized as object-based and usually perform image segmentation as a previous step of classification. The segmentation process aims at recursively split the image into small regions with some physical meaning, which are called objects [2]. If the input segmentation parameters are not fine adjusted, the search for objects frequently leads to undersegmentation or oversegmentation and long processing time. Undersegmentation can frequently causes further misclassification since not all object features are completely preserved into the merged regions. In some cases, the optimal choice of the parameters is somehow difficult and can also vary along the image, harming the segmentation results reached by using a fixed set of parameters. In this abstract we propose a new iterative classification-based segmentation technique to early recognize classes of growing regions by applying decision rules during the segmentation process. Differently from traditional segmentation techniques, in the proposed methodology under-growing regions having meaningful size can be pre-analyzed not only in order to test merging among them, but also in order to test labeling according to predefined classes. To this end, we propose to use parametric relationships according to the statistical nature of images and classes. In this study we use the t-student test to compare between statistical features of growing regions and predefined features of classes samples. By using this simultaneous methodology, growing regions with high class membership probability can be early associated to one of the predefined classes, avoiding, for example, further mislabeling of undersegmented regions in the classification process. Another advantage of the proposed technique is that, since the segments are being analyzed and classified, they are placed out the segmentation process, reducing the processing time. Moreover, at the end of the classification-based segmentation process, remaining non-classified objects can receive a different classification rule in a complementary classification process.

2. CLASSIFICATION-BASED SEGMENTATION TECHNIQUE

The proposed methodology is directed to be applied in a step-wise segmentation process involving growing regions. At this point, the most popular segmentation methodologies are the region-based ones, which include the region growing techniques [1]. These techniques are aimed to determine objects by iteratively merging pixels or regions in the image [3]. They start from the pixel level and apply similarity tests based on input parameters to determine whether two adjacent pixels must be merged or not. Depending on the specific region growing technique, the type and number of input parameters can vary. A common stage to all of the region growing techniques is the comparison between adjacent regions in order to produce larger regions by merging them. The basis of the proposed methodology is to intercept this stage by introducing decision rules aiming at classify provisory regions with meaningful size. The meaningful size of the regions can be defined by the user according to the statistical characteristics of the classes. As mentioned in Section 1, we propose to use the t-student statistical test to compare between growing regions and predefined classes. The t-student test can reject or not the hypothesis of equality of means between two sets of elements with Gaussian distribution. In the natural scenes, which we intend to apply the proposed methodology, it is expected to have classes presenting this kind of distribution.

In our formulation, we consider a multispectral image **X** with M channels and C predefined classes. We supposed to have a set of multispectral samples S_c of each of the C classes. For each sample S_c, we compute the number of elements ne_c as well as the multispectral mean vector $\boldsymbol{M}_c$. We start by applying a region growing segmentation in **X** or in a spectral subset of it. Let us consider two adjacent regions R_i with respective number of elements ne_i and vector of region means $\boldsymbol{M}_i$. If ne_i is higher than a predefined threshold T, we can compute the following statistic for S_c and R_i:

$$t_{i,c} = \frac{\sqrt{\left(\boldsymbol{M}_i - \boldsymbol{M}_c\right)^2}}{\sigma\sqrt{\left(\frac{1}{ne_i} + \frac{1}{ne_c}\right)}} \sim t_v , \tag{1}$$

where $t_{i,c}$ is the t statistic concerning the region i and the class c, σ is the standard deviation of the whole image and t_v is the probability density function of the t distribution with $v = ne_i + ne_c - 2$ degrees of freedom. t_v can be derived from the following equation:

$$t_v = f^{-1}(p \mid v) = \left\{ t : f(t_v \mid v) = p \right\} ,$$

where p is the corresponding confidence level computed using:

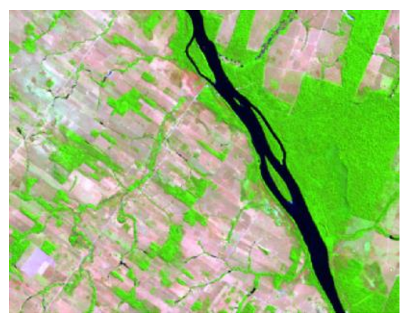
$$p = f(t_v, v) = \int_0^{t_v} \frac{\Gamma\left(\frac{v+1}{2}\right)}{\Gamma\left(\frac{v}{2}\right)} \frac{1}{\sqrt{v\pi}} \frac{1}{\left(1 + \frac{t^2}{v}\right)^{\frac{v+1}{2}}} dt ,$$

where Γ(.) is the Gamma function associated with the t-student probability density function. Thus, regions R_i which satisfies $ne_i > T$ and $t_{i,c} \leq t_v$ with a user defined confidence level p, can be considered belonging to the class c and are not considered in the subsequent segmentation steps anymore. It is important to note that in the case two or more classes satisfies the above mentioned constraints for a given R_i, the region will be assigned to the class having the smallest value of $t_{i,c}$.

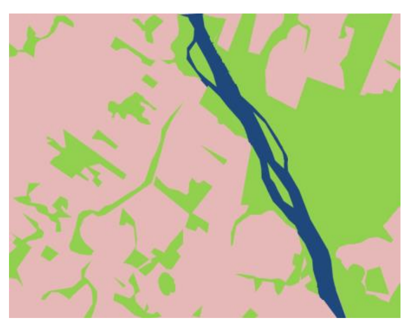
The expected result is a partially classified segmented image. Objects not classified are those which have not presented enough similarity during its process of growing to any of the available classes according the t-student test. These remaining regions can still be inserted into different classification systems in order to complete the classification of the image.

3. EXPERIMENT AND ANALYSIS

In this study we consider a TM-Landsat-5 subset (350×450 pixels) characterized by forest and deforestation activities in the Brazilian Amazon (path/row 227/67). The image was acquired in July/2011. A false color composition of the images is shown in Fig. 1a. The region growing segmentation process performed here follows the basic rules described in [4], and has two input parameters: similarity level and minimum region size. In the present experiment we chose to use 10 and 5 as similarity level and minimum region size, respectively. We also set p = 0.95 for the t-student confidence level and meaningful size T = 100 pixels. We have taken tree different samples corresponding to classes of forest, deforestation and water. All samples had size higher than the threshold T. In order to access the effectiveness of the proposed methodology, we performed two different experiments: (i) by segmenting the image followed by maximum likelihood classification, and (ii) by employing the proposed classification-based segmentation followed by maximum likelihood classification of remaining non-classified objects. The maximum likelihood classifications were performed with the objects mean in each channel. The common parameters used in both cases were the same, as well as, the samples of the corresponding two classes. The ground truth visually built for this experiment is showed in Fig. 1b.



(a)



(b)

Fig. 1. (a) Multispectral TM-Landsat-5 image data employed in the experiment (5(R), 4(G), 3(B)), and (b) ground truth.

The accuracy assessment was conducted by means of global accuracy. The results computed for the traditional object-based classification (segmentation followed by classification) showed a global accuracy of 75%, whereas the global accuracy presented by the proposed methodology was 78%. As expected, the processing time spent by the proposed methodology was lower than the traditional object-based classification.

4. CONCLUSIONS

The results of the experiment indicate strength of the proposed methodology. However, experiments with other areas and other kinds of classifiers are needed to state a more consistent conclusion. We can also mention that, depending on the type and resolution of the image, others statistical tests can be considered.

5. REFERENCES

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