SEGMENTATION AND CLASSIFICATION OF LANDSAT-TM IMAGES TO MONITOR THE SOIL USE

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ABSTRACT: A hybrid unsupervised/supervised classification method is described and applied to Landsat TM images. This method differs from the conventional classification in the sense that the clustering algorithm is applied to a set of regions, obtained from the segmented image. The statistical parameters of these regions are used to classify each. After the previous step, some regions are selects to be training areas on a supervised classification step. A comparison is made between the pixel per pixel classification and the region classification.

1 INTRODUCTION

Know and represent the Earth surface have always been a preoccupation of many civilizations. The increase of complexity of localization, mapping and monitor the planet surface, with the objective of territorial limits protection, knowledge, use and preservation of natural resources, are responsible for the advance in the ways of receiving and manipulating Earth surface information.

Brazil, with it's huge territory, characterized by a great agroecological diversity, combined with a very dynamic soil occupation, presence for decades an extremely disoriented populational flux. The necessity to know, map and monitor natural resources and populational movements, with the objective of a more controlled occupation of the territory and a rationally use of natural resources, have encouraged the execution of projects for researching and map the Brazilian surface (Bognola et al, 1997)

Traditionally, classification techniques have been divided into two big categories: supervised and non-supervised, according to the proceedings used to obtain the training areas. In Brazil, classification techniques, are not used with the same intensity as other countries. That's because of different reasons, for example: processing capacity and storage of great volume of data, the necessity to train teams and the overall performance of these techniques.

Some experiments were done to test segmentation methods in the Amazon area (Almeida, 1994). Although the results were considered satisfactory, these experiments only tested the performance in homogenous areas, where big properties and few variety of soil use are predominant, don't reflecting the huge amount of situation of soil use, that exist in Brazil. The necessity and urgency to know and monitor soil use and natural resources, in the whole country, turn the segmentation and classification tools to be of great interest.

This paper has the objective of showing an hybrid methodology of Landsat-TM images classification. First, a region-growing algorithm is used to divide the image into spectral homogenous regions. Then, a clustering algorithm is applied over the segmented image. The next step is a selection of regions that will be used as training areas on the supervised classification step. The last step is, using the training areas, apply a supervised algorithm and classify the image.

This method differs from the conventional classification methods in a way that a clustering algorithm is applied over a segmented image that was obtained by using region-growing technique. Then a selection of training areas is made and finally a supervised algorithm is applied over the image to obtain a classification.

2 METHOD

The method involved 5(five) different steps: pre-processing (register and contrast), processing (segmentation and classification), verification of the accuracy of the mapping, analysis of the results and elaboration of the final document.

The segmentation technique proposed is object delimitation using region-growing method. Initially, the algorithm labels each pixel as a distinct region. Pixels with similarity values lower than a threshold are united. Later the image is fragmented into sub-regions, they will later be united using another threshold given by the user (INPE, 1996; Khodja et al, 1995; Khodja & Mengue, 1996).

The methodological proceedings of classification were based on two distinct processes that complement each other. The first process used, non-supervised classification, tries to cluster pixels within the same spectral variance (Bognola,1997). The second process, supervised classification, was controlled by the selection of regions that represent each class. It was a sample selection process (Khodja & Mengue, 1996).

2.1 Image Segmentation

During this step the image is divided into spectral homogenous regions. It considers intrinsic characteristics of the image like pixels gray level, texture and contrast (Woodcok et al, 1994).

Segmentation is a process that has the aim of unite regions that have the same properties (Khodja et al, 1995). The algorithm used needs the definition of two variables, a similarity threshold and a minimum size to each region. Imposition of lower similarity will create a great number of fragments in the original image. If the other variable, minimum area is defined bigger than necessary, lots of heterogeneous polygons will be created. In the other way around, high similarity threshold and small minimum areas, will also produce heterogeneous fragments.

Optimum values, to be determined for image segmentation, will depend on the spatial division patterns of the objects in each area. There aren't standard values for these variables. The user has to do lots of approximation to reach an adequate fragmentation level.

2.2 Image Classification

The methodological proceedings of classification are based on two distinct processes that complement each other. First, a non-supervised classification is used, it tries to cluster regions using as criteria the spectral variance. The second process, supervised classification, is controlled by selection of training fields that represent each class.

The non-supervised process is used to select spectral homogeneous areas that will be used, on a second step, as training fields during the supervised classification.

2.2.1 Non-supervised classification. This process will help the selection of training fields in the image. Each pixel will be an homogeneous spectral region. The region-growing algorithm will cluster pixels that have same characteristics.

Only one supposition is associated with the data, they have to obey normal distribution. The equation that represents the observation distribution of each pixel is equation 1:

$$\frac{1}{\left(2\pi|C|\right)^{k/2}}\exp\!\left((y-\mu)^T C^{-1}(y-\mu)\right) \tag{1}$$

where |C| is the determinant of the covariance matrix and μ is the mean vector.

In this way, it's possible to define a Mahalanobis distance between two points $\underline{x}$ and $\underline{y}$ (equation 2):

$$(y - x)^T C^{-1}(y - x)$$

(2)

Supposing that different observations are independent from one another, then the value of the equation 2 is an aleatoric variable with X^2 (Chi-squared) distribution (Bins et al, 1993).
The algorithm consists of three steps. On the first step a region list is ordered in a decrescent way by its area. It's expected that regions with big areas are representative of a class. The threshold, given in percentage, defines a maximum Mahalanobis distance that regions could be far from the class center. In another way, we could say that this threshold define an hiperelypsoid in the attributes space that every region, whose means are inside it, are considered to belong to a certain class. The distance values for each percentual are defined on X^2 table.
The second step is initial classes detection. The proceeding is: get the statistics parameters of the first region of the list as initial parameters of the class. On an iterative process, remove from the list every region whose Mahalanobis distance is lower than a threshold. New statistics parameters of the class are calculated. This process is repeated until is possible to remove regions from the list. The next class is recognized as the same way and the process goes on until the list is empty.
In the previous step, it could happen that a region could be misclassified. In the third step, the regions are classified again using the new centers defined on the previous step, to correct any distortion (Bins et al, 1993).

2.2.2 Supervised Classification. The first thing to do is training fields selection, then the Bhattacharya algorithm is used. The Bhattacharya classificator is a supervised method used to classify segmented images, that is, the object to be classified is not necessarily a pixel but a region in the image. The steps of this classification are the same as the pixel classification. The Bhattacharya distance is traditionally used as a separability measure between classes to select image attributes.
This distance is calculated using the equation 3:

$$B = \frac{1}{8}MH + \frac{1}{2}\ln\left[\frac{|(C_a + C_b)|/2}{\left(|C_a||C_b|\right)^{1/2}}\right]$$

(3)

where, Ca and Cb are the covariance matrix of classes A and B; MH is the Mahalanobis distance defined for two distinct classes using the equation 4:

$$MH = \left[(\mu_a - \mu_b)^T\left(\frac{C_a + C_b}{2}\right)^{-1}(\mu_a - \mu_b)\right]^{1/2}$$

(4)

where, **μ** is the means of each class.

3 EXPERIMENTAL RESULTS

To proceed the experiments, the channels 3, 4 and 5 of the LANDSAT-TM satellite were chosen, The definition of the cartographic scale as 1:50.000 to express the results, considered characteristics like fragmentation patterns and heterogeneity. The area of study was chosen because it was heterogeneous.

The area (figure 1) was 700Km^2 and was limited in the map "Folha Palotina" MI-2-800/3 or SG 22-V-A-I-3, scale 1:50.000.

Figure 1

To define the thematic classes, was necessary to visit the area. Eight classes of soil use and vegetation cover were defined. On the register step, were necessary only 6(six) points of known coordinates as showed in table 4.

CONTROL POINTS	HORIZONTAL ERROR / VERTICAL ERROR (pixels)
1	0.170/ 0.053
2	0.423/ 0.168
3	0.335/ 0.211
4	0.515/ 0.155
5	0.280/ 0.155
6	0.492/ 0.056

Table 1: Erros associated to control points

The great precision and the correspondence existent between points obtained in the map and found in the satellite image, were responsible for the reduced number of control points needed to register the image with errors considered low.

During the contrast manipulation, channel 5 showed an histogram distribution very narrow. The operation used to correct the gray levels was, initially an equalization of the histogram (INPE, 1996), followed by a linear adjust over channel 4. Figures 2, 3 and 4 show the original images and table 2 show image statistics.
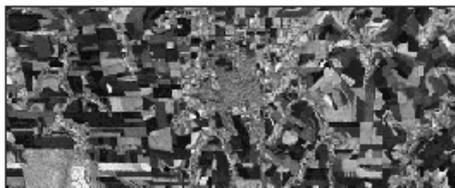

Figure 2. Palotina Channel 3

Figure 3. Palotina channel 4

Figure 4. Palotina channel 5

	MEAN	DESVIO PADRÃO	VARIÂNCE
CHANNEL3	119.33	49.69	2468.85
CHANNEL 4	97.17	53.43	2855.07
CHANNEL 5	127.55	28.32	801.84

Table 2: Image statistics.

After the contrast manipulation, the results are shown on the table 3:

	MÉAN	DESVIO PADRÃO	VARIANCE
CHANNEL 3	130.09	72.47	5251.54
CHANNEL 4	137.70	73.56	5411.66
CHANNEL 5	135.89	72.82	5304.55

Table 3: Image statistics after contrast

During the segmentation step, many approximations were made: degree of similarity of 15, 20, 30 and 35, and minimum area of 30 and 40 pixels. The fragmentation level considered adequate to the study was, degree of similarity 35 and minimum area of 40 pixels. After definition of these thresholds, a segmented image was produced to check if the fragmentation level was adequate or not to the scale used and the reality. In this step, 1162 polygons were found as shown in figure 5.
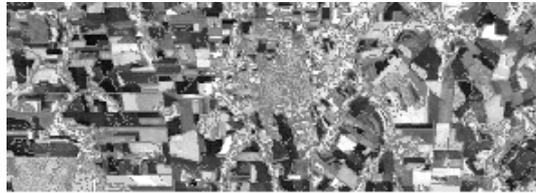
Figure 5. Segmented image

On the image classification step, two distinct processes were used, as mentioned earlier. On the first process, non-supervised classification, the algorithm has as criteria the Mahalanobis distance (INPE, 1996), that is the same as minimum distance, except by the use of the covariance matrix. It was a cluster algorithm. From the segmented image of the earlier step, it tries to find regions that are similar. Using this algorithm 24 distinct regions or classes whose pixels showed similar spectral characteristics were found, as shown in figure 6.
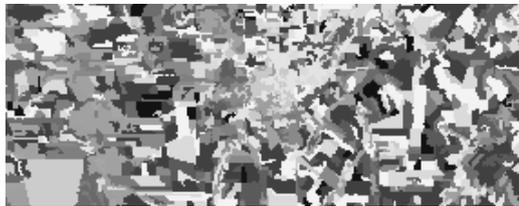

Figure 6. Classified image using cluster algorithm

The second process, supervised classification, used samples of the result obtained in the earlier classification process as training fields. The criteria used was the Bhattacharya distance (INPE, 1996). The results are shown in figure 7.
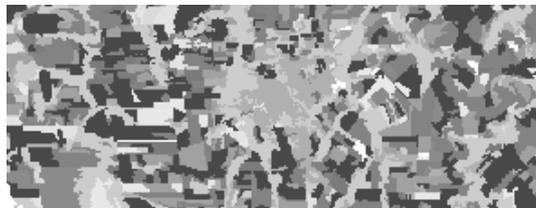

Figure 7: Classified image using supervised classification

By the analysis of the results we find out that the thematic class "urban area" showed the lower percentage of efficiency. That's because the urban area of Palotina City is full of trees higher than 10 meters. The asphaltic surface is cover by the shadows of the trees most of the time. This peculiar characteristic contributes to the lower result on classifying this class and also interfered, with less intensity, in the classification of other classes.

The results obtained by the use of this methodology were compared with the pixel-per-pixel technique of Maximum Likelihood (table 4). The percentage of concordance of correct classified areas between the proposed cluster methodology and pixel-per-pixel classification was 70% (table 5). This reinforces the validity of the proposed methodology.

	Forest1	soil	agricuture 1	agriculture 2	Agriculture 3	Agriculture 4	forest2	urban	Rej
Forest1	94,12%	0	0	0	0	5,88%	0	0	0
Soil	0	100%	0	0	0	0	0	0	0
Agriculture 1	0	0	98,13%	0	0	0	0	1,87%	0
Agriculture 2	0	0	0,32%	90,35%	6,43%	0	0,32%	2,57%	0
Agriculture 3	0	0	0,20%	1,39%	97,43%	0	0	0,99%	0
Agriculture 4	10,62%	0	0	0	0	87,50%	1,88%	0	0
Forest2	2,12%	0	0,47%	1,18%	0	1,41%	84,94 %	9,88%	0
Urban	0	0	6,75%	11,55%	2,40%	0,22%	14,38 %	64,71 %	0

Table 4: Errors matrix of MaxVer method

	Concordância(%)
Forest1	77,27
Soil	87,97
Agriculture 1	69,94
Agriculture2	57,82
Agriculture 3	75,26
Agriculture4	68,01
Forest2	58,37
Urban area	44,39

Table 5: Concordance percentage

6 CONCLUSION

In this work, a methodology of segmentation and classification of Landsat-TM image were presented. First the image is segmented and later, using non-supervised and supervised classification techniques, the image is classified. Another objective of this work was a comparative analysis between the pixel-per-pixel classification and the region classification.

The method presented needs less effort by the user to obtain the concordance levels showed on table 6. That's because there isn't necessary a great number of samples, saving lots of time.

The areas obtained with the segmentation technique using region-growing algorithm, showed better results than the pixel classification. There aren't isolated and non-classified pixels and the limits of the segmented area have few faults.

Concluding, we can consider the general results showed by using region classification were satisfactory, The methodology shows good potential to be used in similarly activities. It could be used as basis to map generation in a way faster than conventional classification.

REFERENCES

ALMEIDA e all. *Mapping Soil Use in Rondônia, Using Segmentation and Classification Techniques in TM Images*. INPE. São José dos Campos , SP, 1994.

BINS, L.S; ERTHAL, G.J.; FONSECA, L.M.G. *Three approaches of Segmenting Remote Sensing Images,* VI Simpósio Latinoamericano de Percepción Remota. Cartagena, Colombia, 3-8, outubro, 1993.

BOGNOLA, I.A. ;MIRANDA, J.R. ;MANGABEIRA, J.A. de C. ; TOLEDO, M.A. , YOSHI, C. *Characterization and mapping of soil use of Jaguariúna County - SP, using geo-processing* , Campinas, 1997.

INPE. Image Processing Department. Manual operation of SPRING: version 2.0.1. São José dos Campos, SP. URL: file:/home/spring/help, outubro de 1996.

KHODJA, A.; HOTYAT, M.; CHATELAIN,A.; GILG, J.P. *Partition dúne image satellitaire et Caractérisarion de son contenu par une Méthode de Segmentation Dímages: Aplication à la Forêt de Bouconne (France) et à la Ville dÓran (Algérie).* Photo-Interpretation, Paris, n. 1995/1, p.25-30. 1995.

KHODJA, A.; MENGUE, A. *Amélioration de láport Thématique d'une Image SPOT XS par les Processus Spatiaux et une Méthode de Segmentation: Application à la région de Lagdo (Nord-Cameroun).* International Journal of Remote Sensing, London, v.17, n.5, p.879-886, 1996.

WOODCOCK, C.; HARWARD, V.J.; *Nested-Hierarchical Scene Models and Image Segmentation.* International Journal of Remote Sensing, London, v.13, n. 16, p.3167-3187, 1992.

WOODCOCK, C.E.; COLLINS, J.B.; GOPAL, S.; JAKABHAZY, V.D.; LI, X.; MACOMBER, S.; RYHERD, S.; HARWARD, V.J.; LEVITAN, J.; WU, Y; WARBINGTON, R. *Mapping Forest Vegetaiton Using Landsat TM Imagery and a Canopy Reflectance Model.* Remote Sensing of Environment, New York, v. 50, n.3, p.240-254, Dec. 1994.