A system for region image classification based on textural measures•

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Abstract. This work presents a system for region classification using textural measures. The user can extract and analyze any kind of textural measures provide by this system and thus classify a group of region samples based on a set of selected measures. The system was developed using IDL and resources from ENVI, providing a user-friendly environment. An example of application of this system for a JERS-1 image is presented in this paper.

Keywords: classification, SAR image, texture

1 Introduction

The satellite images are powerful tools to improve the knowledge of world's natural resources. It is known that these resources are finite and are already being expended at a fast rate, which will increase with the world's rapidly expanding population. In Brazil, several studies have been done to try understanding the Amazonian Forest, with a special interest in the study of secondary succession and its role on the carbon cycle. For many years, Brazilian Amazon Deforestation Survey Project (PRODES) has mapped the deforestation and has estimated the extension and rates of deforestation. This mapping is based on optical images from sensor TM/LANDSAT. But the weather conditions in some regions limit the usefulness of these images. Non-optical sensors can be used to minimize this problem; particularly Synthetic Aperture Radar (SAR) images have been showed to be useful on helping the solution of weather conditions problem. In order to extract the information from these images, it is necessary to develop special tools for processing and analyzing them.

Usually the systems for analyzing images have used only tonal information in the classification process. Yanasse et al. (1993) and Yanasse et al. (1997) showed that tonal average was inadequate to discriminate old stage of regeneration from primary forest areas using C-band SAR data. However, the same authors obtained improvements in the discrimination between these classes when the coefficient of variation was used (Luckman et al., 1997; Yanasse et al., 1993). Texture is an important characteristic for the analysis of many types of images, in special, for SAR images. Unfortunately, there is not a formal approach or precise definition of textures.

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Nevertheless, various authors have tried to quantify it. Methods for textural analysis have been developed using spatial frequency patterns (Chen, 1990), first order statistics (Hsu, 1978, Irons and Petersen, 1981) and second order statistics (Haralick et al., 1973, Welch et al., 1990). Some textural measures do not make assumptions about the statistical distribution of the data and thus they could be taken from either radar or optical data. Yanasse et al. (1993) and Frery et al. (1997) studied some statistical distributions from radar data and concluded that some parameters of these distributions was related with textural information and could be used to discriminate land use classes.

This work presents a system developed at the National Institute for Space Research (INPE) for region classification using textural measures. The description of the system is presented on Section 2. The classification of a georeferenced JERS-1 image is presented as an example of the use of the system (Section 3).

2 The system

The system provides a user-friendly environment to extract and analyze textural measures from images, and classifies regions based on pre-selected measures. It was developed using IDL (Interactive Data Language) and functions from ENVI (Environment for Visualizing Images) system. The procedures were developed using a windows system where the user can easily find the functions of interest (**Figure 1**).

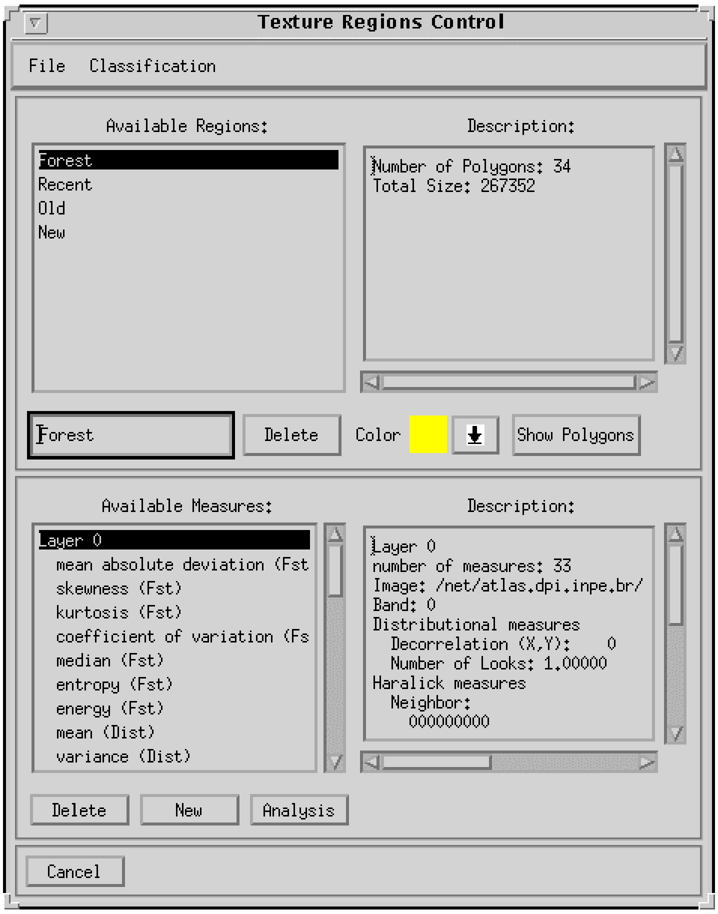

Figure 1: Main interface.

Initially, the user must select samples from each class of interest. In fact, each sample is a polygon formed by one or more pixels from the image. A “region” is formed by joining samples from the same class. The regions can be taken by selecting image subsets drawn by the user (using ENVI’s resources) or from segmented images. A segmented image can be defined as an image where each area or polygon is identified by one gray level, different from its neighbors.

The regions must have some samples in order to characterize the dispersion of textural measures. A “layer” is defined as a group of textural measures extracted from the same image and having the same neighborhood configuration pattern. In this form, the system can compare different textural measures from the same image or the same textural measure from different images.

2.1 Textural measures

A set of measures implemented in this system can be split on four groups: first order, distributional, Haralick’s and autocorrelation measures.

The first order measures are calculated without considering spatial distribution of pixels. Seven of these measures are included in this system: mean absolute deviation, skewness, kurtosis, coefficient of variation, median, entropy and energy.

The distributional measures are parameters of statistical distributions, some of them specific for radar data. Eight distributional measures are calculated by this system: estimated mean, variance and standard deviation of Normal and Log-Normal distributions; and estimated α parameter of the K-Intensity and K-Amplitude distributions. For an overview about α parameter estimators, the interested reader can see Yanasse et al. (1993), Frery et al. (1997) and Yanasse et al. (1997) among others.

The Haralick’s measures are based on the Gray Level Co-occurrence Matrix (GLCM). The GLCM describes probabilities of the co-occurrence of two specific gray-levels given specific pixel locations in terms of relative direction and distance. More details about these measures can be found on Haralick et al. (1973), Haralick (1979), Unser (1986) and Welch at al. (1990). Eighteen measures are included in this system: contrast, entropy, energy, homogeneity, correlation, dissimilarity, chi-square, cluster shade and cluster prominence; mean, variance, entropy and energy of the sum and difference vectors; and contrast of the difference vector.

In this system, the autocorrelation spatial measures can be defined from lags–4 to 4, in row and column directions. Also, the system permits to calculate ratios between two different autocorrelations.

2.2 Analysis of textural measures

The textural measures have a variable range of values and thus it is necessary to standard each one of them. Thereby the measures are linearly stretched, ranging from zero (minimum value) to one (maximum value), considering all classes of interest. It is important to pay attention to the presence of outlier values that must be eliminated before standardization. The user can analyze each measure and redefine its range in order to discard outlier values. The interface for making this analysis is shown in **Figure 2**, for the particular case of the data mean. The abscissas refer to

FIG. 2

the classes of interest, and the ordinates to the measure values (original on the left plot and standardized on the right plot).

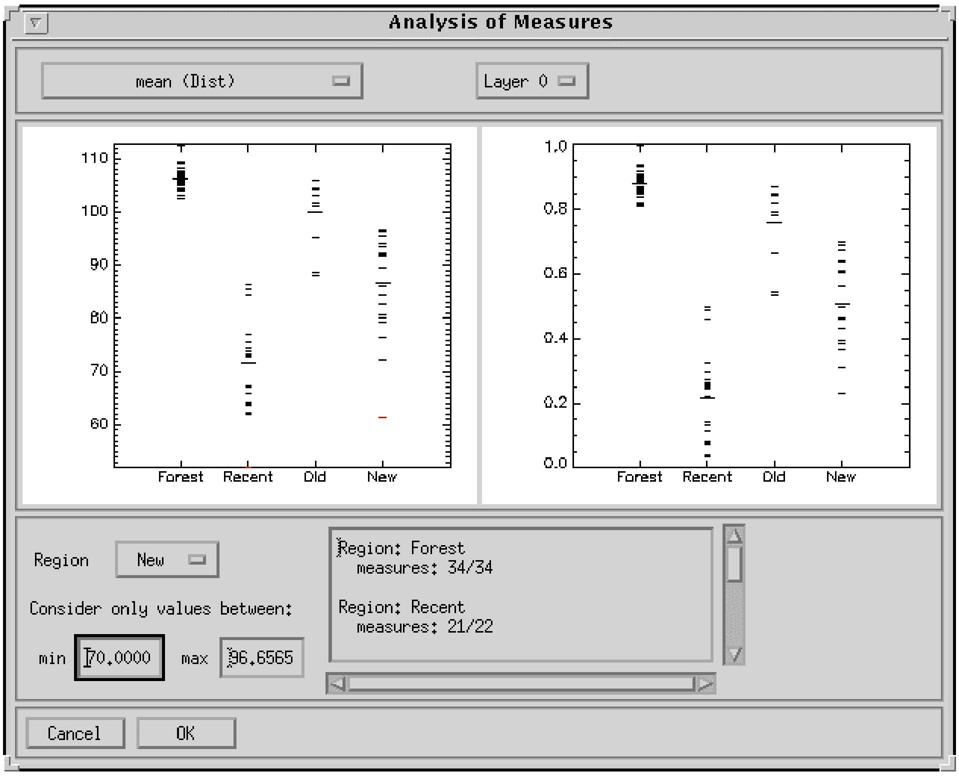

Figure 2: Interface for measure analysis.

2.3 Selection of textural measures

It is evident that a large number of measures can be extracted and become impracticable to use all of them in the image classification. The decision rule to choose one or more measures can be based on discriminant factor, which evaluates the separability between classes. The discriminant factor adopted in this system is calculated using the variation within and between two classes and given by:

$$DF_{AB} = \frac{n_A . \sum_{i=1}^{n_A} \left(X_{Ai} - \overline{X}_A \right)^2 + n_B . \sum_{i=1}^{n_B} \left(X_{Bi} - \overline{X}_B \right)^2}{n_A . \sum_{i=1}^{n_A} \left(X_{Ai} - \overline{X}_B \right)^2 + n_B . \sum_{i=1}^{n_B} \left(X_{Bi} - \overline{X}_A \right)^2}$$

where, $X_{\omega i}$ is the i^{th} sample of class ω, $\overline{X}_\omega$ is mean value of class ω, n_ω is number of samples of class ω. Thereby there will be one measure with maximum discriminant factor for each combination of classes. For example, if there are 4 classes, there will be until 6 selected measures. The window of the system that shows the pairs of classes and its selected discriminant factor is illustrated in **Figure 3**. FIG. 3

After selecting the textural measures, the mean vector, the covariance matrix and some characteristics of each class and of standardization process are saved in a file (called training file) which will be used on the classification process.

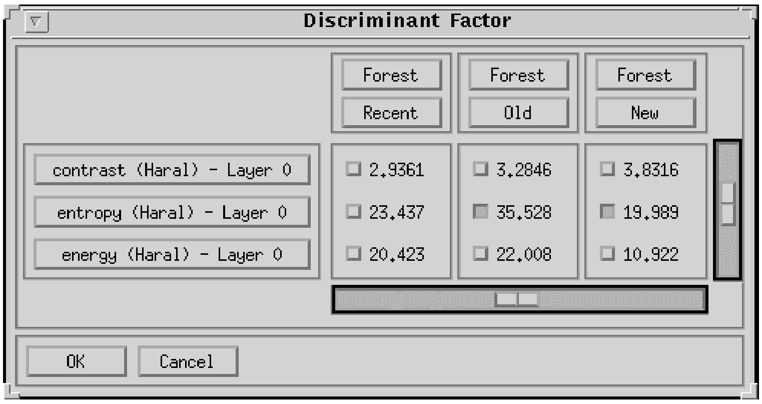

Figure 3: Interface for selection of measures based on discriminant factor.

2.4 Classification

The classification initiates by selecting the training file. If one of the selected textural measures would not have been extracted, the system will do it before the classification. Each polygon of each region will be classified as belonging to the class of interest that minimizes the Mahalanobis distance.

After classifying all polygons, the system will build an image, by painting the pixels from each polygon with the color of the class designed to it. The visualization as well as the evaluation of the classified image can be done using ENVI's resources.

3 An example of application on JERS-1 image

The potentiality of system is demonstrated by using a georeferenced JERS-1 image from 06/26/1993, L band, HH polarization and amplitude data. The size of this image is 903 samples per 1980 lines and the pixel resolution is 30 m. **Figure 4a** illustrates a piece (400x400 pixels) of this image. This image surrounds the Tapajós National Forest (FLONA), Pará State, Brazil (54^{o}01'48" to 55^{o}49'33" WGr, 02^{o}56'37" to 03^{o}23'30" S). The FLONA region has large areas of tropical forest that have been cleared and converted into pasture and agricultural fields. Some of these areas were abandoned, becoming a secondary succession.

FIG. 4a

Four classes of interest were established in this work: primary forest (PF), areas without anthropogenic action; old secondary forest (OSF), areas abandoned for more than 7 years old; new secondary forest (NSF), areas abandoned for less than 7 years old; and recent activities (RA), others land uses, e.g., bare soil, pasture and agricultural fields.

Samples for each class of interest were chosen based on a land use map (**Figure 4b**), built from a multi-temporal LANDSAT/TM images from 1984 to 1993. The methodology used for building this map is describe in Sant'Anna et al. (1995). The number of collected samples and total number of pixels belonging to each class are shown in **Table 1**

FIG. 4b

TAB. 1

All first order measures, all distributional measures (except *a* parameter of the K-intensity distribution), all Haralick's measures (using the 8 nearest neighbors to calculate the co-occurrence matrix), the autocorrelations with Lags (1,0) and (1,1), and the ratio of these two autocorrelations (Lag (1,1)/Lag (1,0)) were extracted for each sample.

Table 1: Information about training samples.

Class of interest	Number of polygons	Total number of pixels
PF	34	267,352
OSF	11	3,561
NSF	20	13,102
RA	22	11,566

Table 2 shows the 3 best measures according to the discriminant factor for each pair of classes. It can be observed that the largest discrimination occurred between PF and OSF classes using Haralick's entropy. This result is very important because these classes are not separable when using only mean value (Yanasse et al., 1993; Yanasse et al., 1997). The PF and RA classes are also well discriminated, showing a large discriminant factor value. The smallest discriminant factor value was found for the pairs OSF/NSF and NSF/RA, indicating that these classes are poorly separable.

Table 2: Discriminant factor for each pair of classes of interest.

	Pair of classes of interest*					
	PF/OSF	PF/NSF	PF/RA	OSF/NSF	OSF/RA	NSF/RA
Median	7.09	14.66	33.19	2.29	7.20	3.13
Haralick's entropy	35.53	19.99	23.44	2.28	1.59	1.17
Haralick's correlation	1.12	4.40	4.14	2.69	2.31	1.04

*The marked values indicate the measure selected for pair of class.

The result of the classification using the 3 best selected measures is shown in **Figure 4c**. It can be noted that many polygons of RA were misclassified as NSF and a large number of little polygons was classified as OSF when, in fact, should be classified as NSF. FIG. 4c

To improve this result, the selection of measures and classification was done in 2 steps. In the first one, PF was joined to OSF and NSF was joined to RA, creating 2 groups. The median was chosen in the selection process as the best textural measure to discriminate among these groups, with a discriminant factor of 10.10. A classification was performed to separate these 2 groups. In second step, the polygons from each group were classified on one of the classes that forms the group using the measure selected for that pair (Haralick's entropy to PF/OSF and median to NSF/RA). The result is shown in **Figure 4d**. A visually improvement on the classification can be seen, when comparing the two classified images with the land use map. FIG. 4d

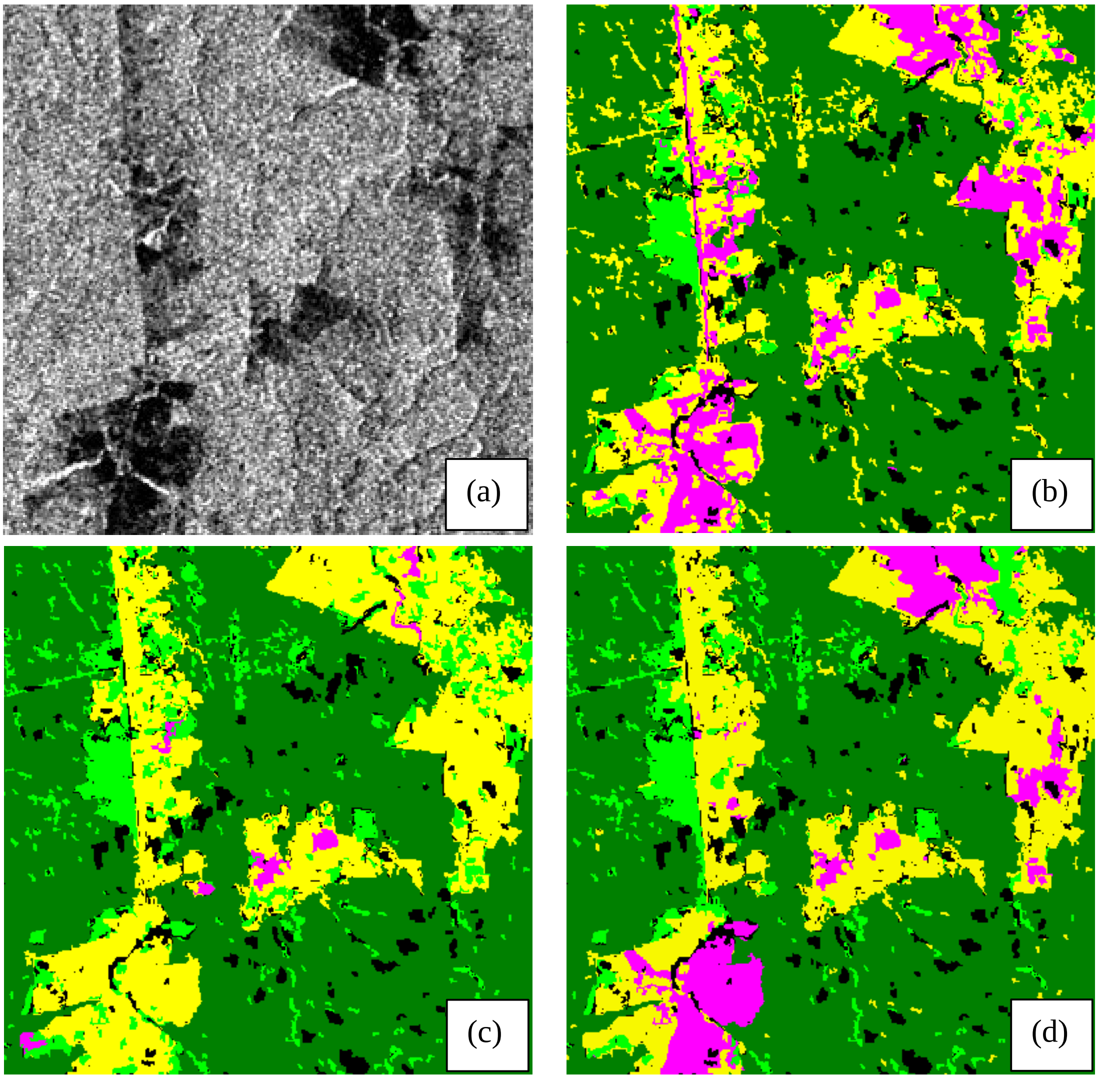

Figure 4: (a) Piece of original JERS-1 image; (b) Regeneration Stage Map; (c) Result of classification based on 3 textural measures (median, Haralick's entropy and Haralick's correlation); (d) Result of classification based on 2 textural measures (median and Haralick's entropy) performed in 2 parts. Dark green is primary forest (PF), light green is old secondary forest (OSF), yellow is new secondary forest (NSF) and magenta is recent activities (RA).

4 Conclusion and further work

This work presented a system for region classification using textural measures. The system gives to the user the possibility of extracting and analyzing many types and configurations of textural measures. The user may test the discriminatory power of a measure and study the variation of this discriminatory power when any characteristic is changed (polygon size, image type, etc).

The textural information carried on images are very important to the comprehension of its complexity and must not be ignored on the classification process. This importance can be indicated by the results obtained in this work.

The inclusion of new measures into the system is possible due to the simple computer language used on its implementation. Other methods for measure selection may also be implemented. Finally, the system can be adapted to permit the use of textural filters. In other words, this system can be easily upgraded.

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