Spectral Analysis, Computational Intelligence and Knowledge Integration for Automatic Pattern Recognition from Multispectral Scenes

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Abstract — Each year near 1PB, on average, of new data, arising from remote sensing, mainly from multispectral imaging sensors, are added to the already extraordinary mass of existing data about the Earth's surface. This massive amount of raw data requires computational tools that allow automatic recognition of desired patterns (geographic objects of interest) quickly and concisely. Therefore, is proposed that such recognition is performed through Spectral Analysis and Computational Intelligence (CI) integration, based on knowledge gained by image experts. These techniques integration will be applied to the spectral signatures – formed by the quantization levels of the pattern in each spectral band – of each pattern of interest, using almost all spectral information available, as the experts do. Despite of the stage of work is in the CI algorithms testing phase, the preliminary results achieved from algorithms SOM (Self-Organizing Maps) and ANFIS (Adaptive Neuro-Fuzzy Inference System) produced average correct classifications.

Keywords-component: remote sensing; automatic pattern recognition; computational intelligence; spectral signature; landsat.

I. INTRODUCTION

This paper is a formal presentation of the current stage of doctorate thesis research, which is in its second year of study, developed in Environmental Monitoring and Control Research of the Environment Science at Universidade do Estado do Rio de Janeiro (UERJ).

A. *Motivation and Description of the Problem*

As, in essence, spectral imaging, either orbital or airbone, captures the information in a scene [1], digital registers contain the spectral information of the state of each object in the scene, at the moment of capture. The orbital imaging sensors have different ranges of spectral bands, in addition to the visible range, increasing further the amount of spectral information available in the scene. Therefore, these information are essential to a more complete identification of these objects, which leads to the need for knowledge of spectral patterns (which will compose the signatures on several bands, the spectral signatures of objects) to be significant for a correct classification [2].

References [1,2,3,4,5] show that the analysis and interpretation of a multispectral scene need specialists in these classes. This fact implies in many hours of application, as well as probability, so that a portion of surface area [2] has its objects properly analyzed and characterized, in the visual manner (the image is interpreted) by one or more professional based on their acquired knowledge and, if possible, on available data of the area. These professionals are divided into two categories: the experts, with large experience, who perform the subjective visual analysis objects, which requires a long working; and the specialists, with experience but make the objects classification based on specialists programs, possessing a smattering of visual interpretation and a knowledge of these programs operation, without, however, formal knowledge of the algorithms used in classification.

When using any of the professionals mentioned above, there are, generally, two possible outcomes: a delayed classification with a good quality of interpretation, or a quickly classification with a dubious quality interpretation. In any of the results, there is always loss: in time or in quality. Then the need to develop computational tools that allow extracting the necessary information more quickly (as computer do) and accurately (as experts do) from multispectral scenes is essential.

B. *Relevance*

Currently, the knowledge of spectral signatures is essential to carry out environmental impact assessment, inventory and management of natural resources, crop forecasting and pest control, classification of military targets, among others. Thus, a classifier system of spectral patterns that work with multiple digital registers and allows the addition and learning of spectral objects behaviors knowledge is highly desirable and beneficial. Thus, it contributes to several areas of knowledge such as Engineering, Geology, Geography, Biology, Management, Administration, Agriculture, Forestry and Defense, covering, thereby, both the scientific community, as the military, beyond the commercial area and public services.

C. Objectives

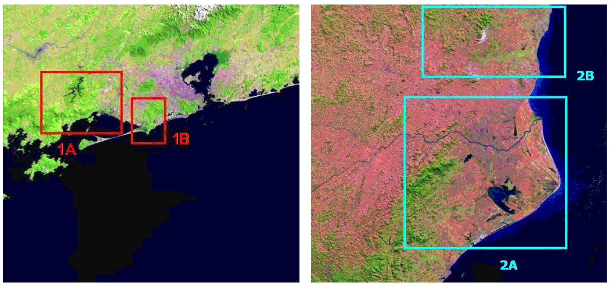
Proposals a Spectral Analysis (SA) and Computational Intelligence (CI) integration technique for automatic pattern recognition in multispectral orbital images, with implementation of these techniques according to the expert's knowledge. This integration will be validated through test areas. The aim is to achieve automatic pattern recognition in extent that the database is enlarged, by analyzing and learning acquired from the entry of new data concerning to the geographic objects of interest (in this study, six classes). In order to automate the processing tasks, will be implemented a prototype program.

II. MATERIALS AND METHODS

A. Database

The scenes used are from Landsat-5, with all the seven bands, with level 2 correction (GEOTIFF format – Geographic Tagged Image File Format), indicating that they have both a reasonable geometry and radiometry for the pattern analysis proposes in the study. The spatial or geographic reference (also known as registration) is a transformation that links the grid of pixels (a pixel array consisting of rows and columns) with the corresponding coordinate's grid on the ground. This transformation is not a concern of the proposed study, since this reference does not add any value to the pattern classification. In fact, the algorithms commonly used for spatial referencing perform resampling of image pixels, which causes significant changes in the levels of quantization of pixels.

In this study is used only six bands – 1, 2, 3, 4, 5 and 7 – because the sixth band (thermal infrared) in Landsat-5 has 80m of spatial resolution, instead of the 30m on the others bands, which made its use impracticable in spectral analysis.



(a) (b)

Figure 1. (a) Scene 1 (217/76 – RJ); and (b) Scene 2 (216/75 – ES).

The two test areas, 1 and 2, were established in the southeast, specifically in state of Rio de Janeiro (RJ) and in state of Espírito Santo (ES), due to proximity and expert's knowledge, as well as increased availability of environmental data (needed for the study of pattern classification). The scenes chosen (orbit/scene) are the 217/76 (RJ) and the 216/75 (ES), and Fig. 1 show them with the respective cuts for analysis.

B. Integration Proposed

To solve the problem of automatic pattern recognition from multispectral sensors is remarkable the following keywords: nature, knowledge and modeling. The correct correlation and interaction between these elements of this triad is the answer to be pursued. Knowledge came from the experts, which must be thoroughly understood so that the modeling is the most accurate. The same happens with nature, which consists mostly of uncertainty and complexity, which leads to a multidisciplinary approach. Therefore, is not possible to expect good results from methods using only logical reasoning, linear and, essentially, monodisciplinary to solving problems involving nature.

The CI is a research area that aims to replicate human thought through computational methods, trying to simulate the human ability to solve problems and accomplish tasks. CI techniques provide the learning of knowledge as the entry of new data, just like humans [6]. The Artificial Neural Networks (ANN) is one of the CI techniques which represents a mathematical model inspired by the structure of human brain neurons and that "acquire" knowledge through experience. The Fuzzy Logic (FL) has the ability to infer conclusions and generate responses based on vague, ambiguous, imprecise and incomplete qualitatively information, assuming logical intermediate values between falsehood and truth: an assumption varies in degree of truth (or falsity) from 0 to 1, which generates assumptions partly true or partly false [7]. Thus, systems that use this logic has the ability to associate in a way similar to humans, since it works with mathematical models dedicated to the treatment of uncertainty.

As the complexity can be modeled by analyzing the spectral behavior of geographic objects, the uncertainty can be modeled by FL and learning by ANN. As both FL and ANN can model the expert's knowledge, a classifier system specializing in spectral patterns can be built. The rudimentary scheme of the integration is shown in Fig. 2, which has the following modules:

- A Spectral Analysis DataBase (SADB) module implemented with defining parameters for each band of the sensor used, for the values and radiometric correlations of the desired classes [8].
- A Artificial Neural Networks (ANN) module implemented with the quantizations defined by bands and desired classes, with the expert's knowledge .
- A Fuzzy Logic (FL) module implemented with the quantizations defined by bands and desired classes, with the expert's knowledge, so that sets of rules are generated [9].
- A Decision Maker (DM) Module where will be compared the outputs of the ANN and FL modules: if exists quantitative differences, the DM will readjust the quantization values in SADB, without creating new classes; if exists qualitative difference, the DM will generate a user report, so that, if desired, can be introduced a new classification.

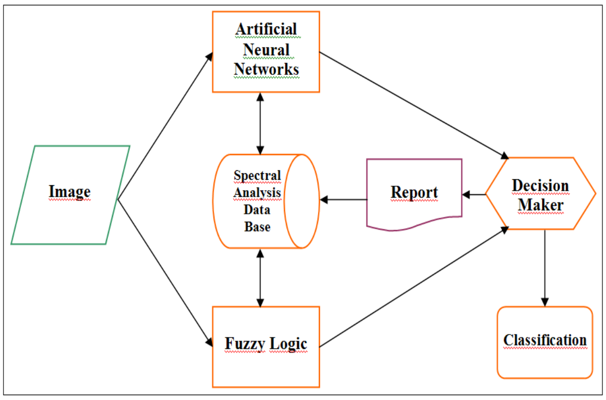


Figure 2. Rudimentary scheme of the study [9].

III. Steps Performed and Ongoing

Following, will be described the steps in progress.

A. *Spectral Analysis Performed*

The spectral behavior of an object is variable due to environmental variables (temperature, humidity, rain, snow, wind, sunlight, season, among others), intrinsic physical factors (own structures of objects such as composition, oxidation and aging), extrinsic physical factors (such as sunlight, stress, fatigue, flood, etc) and anthropogenic factors [3,9]. Thus, such behavior is extremely changeable, making the existing commercial software, grounded on average spectral curves, in standard band fusions, greatly limited and tending to error. Therefore, the use of a greater number of available bands is essential to a better objects characterization, leading to the need for full knowledge of all the spectral patterns of each geographic object, i.e., the spectral signature of the desired objects in a scene, considering the interactions between the different bands.

Spectral analysis of the images is mainly based on the image pixels, their relationship neighborhood and in expert knowledge in order to provide parameters to CI techniques. Therefore, it is established that each class will be represented in the Spectral Analysis DataBase (SADB) by their spectral signatures. Each signature consists of the quantization levels present in the six bands for the same representative pixel of a particular class (Fig. 3). So, the spectral signature will be a line-vector (1) whose elements are formed by the quantization levels of the pixel at each particular band, as the length of the vector equals the number of bands used (six elements), following the conformation:

$$SS_m\,(\text{class}) = [\, b_1, b_2, b_3, b_4, b_5, b_7] \qquad (1)$$

where: SS = Spectral Signature;

class = forested area, urbanized area, sand, mangrove, water and water with particulate matter;

m is the signature number, $m = [1, 50]$, $m \in \mathbb{N}$;

$b_n = [0, 256]$, $b_n \in \mathbb{N}$; and

n is the Landsat-5 band used.

The image 1A and 1B are being used by the expert to make a classification oh each area. As the knowledge of the expert has to be modeled, is necessary to monitor every step taken by her, which requires a lot of hard work. This stage of study is taking longer than expected, but, at the same time, it needs to be very careful for a good achievement in mathematical methods of CI techniques.

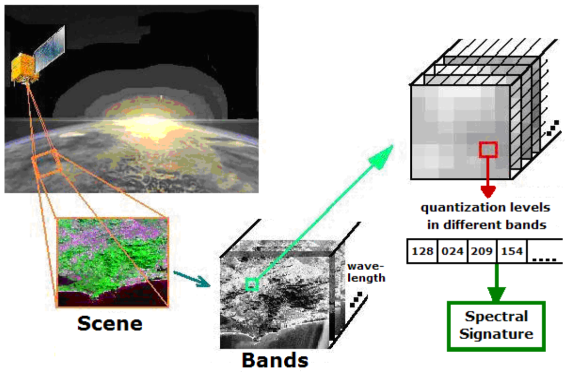


Figure 3. Extraction of the spectral signature proposal [9].

The six classes chosen for the study were: forested area, urbanized area, sand, mangrove, water and water with particulate matter. Initially, for each of these classes were selected 10 unequivocal representative's pixels of each class, but, at the end of the analysis, will be chosen a total of 30 pixels. These pixels are essential for good performance of the SADB, ANN and FL modules.

B. *Test of ANN Algorithms*

The research and literature review further indicated that the application of the SOM (Self-Organizing Maps) technique, from Prof. Teuvo Kohonen, in multispectral images [10,11,12,13] presents very promising results, so that this technique is the first to be tested for the Artificial Neural Networks module (ANN) of the prototype.

Although the spectral analysis has not completed, the tests with the SOM network has already begun, with the end of the test expected for 60 days. Despite the incompleteness of current data, the preliminary tests show promising results (average correct classification near to 79%, at this stage of development).

C. *Test of FL Algorithms*

The research and literature review further indicated that the application of the ANFIS (Adaptive Neuro-Fuzzy Inference System) [14,15,16], in multispectral images, presents very promising results. Due to the encouraging results found by [9], the ANFIS technique is the first to be tested for FL module.

Despite the incompleteness of current data (the full classifications will be completed in 25 days), was used four classes (forested area, urbanized area, mangrove and water) for the preliminary tests with ANFIS technique.

The rules set implemented expresses a simplified model of the experts' work which used all six bands of the sensor available. The preliminary classification (Fig.

4) shows the red color for urbanized area, the green color for forested area, the yellow color for mangrove and blue color for water. The black color indicates the pixels that do not fit into any of the four studied classes.

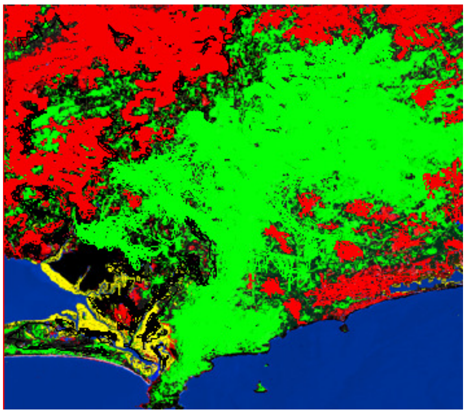


Figure 4. Preliminary classification with ANFIS technique .

A Tab. 1 shows the percentage of correct pixels classifications obtained in preliminaring test, by the ANFIS algorithm. As this algorithm has the worst performance for mangrove class, the rules set implemented is being reviewed.

TABLE I. PRELIMINARY ANFIS CLASSIFICATION RESULTS

CLASSES	CORRECT PIXELS CLASSIFICATIONS
Forested Area	81.%
Urbanized Area	79 %
Mangrove	65 %
Water	90 %

IV. FUTURE STEPS

By the end of this year will be defined the algorithms that will be implemented in the ANN and FL modules. Next year, with the prototype program ready, the prototype classifications will be confronted with the classifications made by the expert and by three business computer systems (chosen among those most used for data imaging processing by remote sensing). These comparisons will be carried out both in processing time and in measuring results, in the test area 2 (Espírito Santo), with field trips scheduled to verify the ground reality.

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REFERENCES

[1] T. M Lillesand and R. W. Kiefer, Remote Sensing and Image Interpretation, 3rd ed., USA: John Wiley & Sons, 1994.

[2] E. D. Conway and The Maryland Space Grant Consortium, An Introduction to Satellite Image Interpretation, USA: The John Hopkins University Press, 1967.

[3] P. R Meneses and J. da S. M. Netto, Sensoriamento Remoto – Reflectância dos Alvos Naturais, EMBRAPA, Brasília, DF: UnB; Planaltina: EMBRAPA Cerrados, 2001.

[4] Robert A. Schowengerdt, Remote Sensing: Models and Methods for Image Processing. 2nd ed., USA: Academic Press NY, 1997.

[5] R. C. Gonzales and R. E. Woods, Processamento de Imagens Digitais, São Paulo, Brasil: Editora Edgard Blücher LTDA, 2000.

[6] S. Haykin, Redes Neurais – Princípios e Prática. 2ª. edição. Porto Alegre: Bookman, 2001.

[7] L. A. Zadeh, Fuzzy Sets, Information and Control, 1965.

[8] K dos S. Teixeira, Banco De Dados de Assinaturas de Registros Digitais Obtidos por Sensoriamento Remoto: Uma Proposta de Conteúdo, Monografia de graduação em Engenharia Cartográfica, Faculdade de Engenharia, Universidade do Estado do Rio de Janeiro (UERJ), 2008.

[9] K dos S. Teixeira, Estudo da Viabilidade da Classificação Automática de Imagens baseada em Registros Digitais e em Inteligência Artificial, Rio de Janeiro. Universidade do Estado do Rio de Janeiro (UERJ). Mestrado em Engenharia da Computação – concentração em Geomática. Faculdade de Engenharia; 2004.

[10] T. Kohonen, Self-Organizing Maps, Springer, Berlin, 3rd ed., 2001.

[11] M. L Gonçalves, M. L. Andrade Netto, J. Zullo Junior, Um Sistema Neural Modular para Classificação de Imagens Utilizando Mapas de Kohonen, In: VII Simpósio Brasileiro de Sensoriamento Remoto, Salvador, 1996, pp. 845–850.

[12] E. Mernyi, The Challenges In Spectral Image Analysis: An Introduction And Review Of ANN Approaches, In Proc. of European Symposium on Artificial Neural Networks (ESANN'99), Brussels, Belgium, 1999, pp. 93-98.

[13] H. Yuan, C. Van Der Wiele and S. Khorram, An Automated Artificial Neural Network System for Land Use/Land Cover Classification from Landsat TM Imagery, Remote Sensing, 2009, pp. 243-265.

[14] Y. Wang and M. Jamshidi. Multispectral Landsat Image Classification Using Fuzzy Expert Systems. Image processing, Biomedicine, Multimedia, Financial Engineering and manufactiuring, vol. 18, pp. 21-26, TSI press, Albuquerque, NM, USA.

[15] D. Stathakis and A. Vasilakos. Comparison Of Computational Intelligence Based Classification Techniques For Remotely Sensed Optical Image Classification. IEEE Transactions on Geoscience and Remote Sensing. Vol. 44, issue 8, Aug. 2006, pp. 2305-2318.

[16] T. B. Cazes, R. Q. Feitosa and L. F. G. Rego. Incorporação de Conhecimento do Especialista Através de Regras Para A Classificação de Imagens de Sensores Remotos de Alta Resolução. In: SIMPÓSIO BRASILEIRO DE SENSORIAMENTO REMOTO, 13. (SBSR), 2007, Florianópolis. Anais... São José dos Campos: INPE, 2007. p. 5659-5666.

[17] DGI/INPE – Catálogo de Imagens, Imagens dos satélites Landsat-1, Landsat-2, Landsat-3, Landsat-5, Landsat-7, CBERS-2 e CBERS-2B (Satélite Sino-Brasileiro de Recursos Terrestres). [Internet] Instituto Nacional de Pesquisas Espaciais – INPE. 2009. Accessed on June 12, 2009. Available at: http://www.dgi.inpe.br/CDSR/.