CARTOGRAFIA DE USO E OCUPAÇÃO DO SOLO

Classificação vectorial com redes neuronais orientadas para objecto

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PALAVRAS CHAVE: Objectos, segmentação multiresolução, dados auxiliares, redes neuronais

KEYWORDS: Objects, neural networks, multiresolution segmentation, ancillary data

RESUMO

Os elementos dinâmicos envolvidos em processos espaciais são o resultado da integração de factores físicos, demográficos, económicos e políticos, e podem ser vistos como detentores de um papel de suporte na interpretação e na formalização de cartas de uso e ocupação do solo. A informação espacial é estruturada de acordo com as classes resultantes da interpretação de áreas "homogéneas", conduzindo à identificação de formas e processos espaciais.

As formas e as estruturas espaciais encontrados são dependentes de factores como o tipo de dados, as técnicas usadas e a informação a ser extraída. O nível do detalhe a incluir e o grau de precisão dos resultados são dependentes dos objectivos finais especificados, e nesta fase estão subjacentes ao conceito da generalização semântica e gráfica dos dados a ser processados. Num ambiente urbano, por exemplo, a heterogeneidade do espaço resulta num sistema complexo, tendo em conta definição das metodologias e dos dados a utilizar. A variabilidade da escala é, frequentemente e ao mesmo tempo, uma causa e um resultado das técnicas e dos métodos que são desenvolvidos.

Os mapas do uso do solo são a representação de uma realidade complexa, com a qual procuramos identificar objectos e atribuir significados ao papel das unidades espaciais.

O aumento na resolução espacial dos satélites e o detalhe contido desse modo numa imagem trouxeram novos contornos à cartografia de uso e ocupação do solo, numa escala grande e com posterior (sub)divisão adicional da nomenclatura a ser utilizada. Entretanto, a classificação automática e/ou semiautomática ainda não fornece o detalhe desejado, principalmente nas áreas fundamentalmente heterogéneas, como se verifica nas áreas urbanas. Esta dificuldade não está somente ligada à complexidade geométrica/espacial destas áreas mas também à complexidade semântica das suas entidades físicas - isto é a identificação de algumas classes do uso não depende tanto das características físicas de seus objectos, mas das funções a elas atribuídas. As abordagens adoptadas, ao nível do pixel, apresentam as suas próprias dificuldades, porque trabalham sobretudo na área da resposta espectral presente na imagem, quando a diferenciação empírica destes mesmos objectos incorpora outros elementos inerentes à natureza física e social do objecto.

Tentando resolver este problema, a detecção remota e os SIG estão a ser cada vez mais usados para desenvolver fontes úteis de informação. Mas o ambiente urbano, por causa de sua paisagem heterogénea e dinâmica, tem sido exigente à aplicabilidade destes métodos e tecnologias. Auspiciosamente, as inovações modernas nos dados, nas tecnologias, e nas teorias municiaram os cientistas e utilizadores com o conhecimento necessário para o estudo de áreas urbanas complexas.

Além disso, as abordagens às classificações baseadas em árvores de decisão, regras de conhecimento e, especialmente, redes neuronais têm apresentado alguns resultados promissores. As redes neuronais apelam particularmente para a classificação supervisionada devido à sua natureza não paramétrica e capacidade de aprender por exemplo. Além disso, geralmente classificam o uso e ocupação do solo com mais exactidão do que as abordagens mais tradicionais. No entanto, ainda persistem alguns problemas e as aplicações geralmente não atingem uma exactidão muito melhor do que 80%.

Assim, são necessários métodos para melhorar o processo de classificação de uso e ocupação do solo, para que este decorra de forma correcta. Este trabalho pretende avaliar o potencial de aumentar a informação sobre o uso e ocupação do solo através de uma aproximação orientada para objecto, utilizando para o efeito uma rede neuronal para classificação da imagem. Especificamente pretende mostrar que usando dados espectrais, de textura e contexto, e auxiliares (estatísticos), é possível, sobre uma base do vectorial, produzir uma classificação que possa apropriadamente representar o uso e ocupação do solo.

A área do estudo está localizada no município de Almada, situada na margem Sul do Rio Tejo a uma das regiões centrais da Grande Área Metropolitana de Lisboa. Os dados usados foram imagens SPOT HRVIR de 2004, fundidas com imagem pancromática em supermodo (resolução espacial de 2,5 m) e os dados estatísticos referenciados à subsecção estatística. O procedimento desenvolvido é baseado em 4 fases: (i) estratégia da segmentação do multiresolução da imagem para a construção de objectos a diferentes escalas, que têm boa similaridade com a forma dos objectos finais de uso e ocupação do solo (polígonos); (ii) aquisição dos atributos dos objectos, principalmente, contexto, textura, informação espectral, forma, entre outros; (iii) aquisição dos dados auxiliares – estatísticos – e (iv) integração dos diferentes tipos de dados dentro de uma rede neuronal para a classificação dos polígonos e a posterior análise discriminante das unidades espaciais de uso e ocupação do solo.

ABSTRACT

In this paper is presented a land use/cover classification methodology of the rural/urban fringe, by means of the application of a neuronal network, with resource to the multiresolution image segmentation, construction of complex elements through object oriented analysis and integration of not spectral (ancillary) information. The study area is the municipality of Almada, located in the south bank of Tagus River and corresponding to one of the core regions of the Lisbon Metropolitan Area (Portugal). The data used was 2004 HRVIR SPOT images fused with supermode panchromatic image and the Portuguese urban quarter statistical data. The developed procedure is based in five steps: 1) Legend creation; 2) deriving statistical ancillary data; 3) deriving object (texture) data; 4) deriving spectral data and 5) neural network classification.

[ST 3]: Aplicações da Detecção Remota (Earth observation)

INTRODUCTION

The dynamic elements involved in spatial processes are the result of the integration of physical, demographic, economic and political factors, inter alias, and can be seen to provide a supporting role in the interpretation and formalization of land use maps. Spatial information is structured according to classes of land use resulting from the interpretation of "homogeneous" areas, leading to the identification of spatial forms and processes.

The spatial forms and structures encountered are dependent on factors such as the type of data, techniques used and the information to be extracted. The level of detail to include and the degree of precision of the results are dependent on objectives specified at the outset, and at this stage are subjacent to the concept of semantic and graphic generalization of the data to be processed. In an urban environment, for example, the heterogeneity of the space results in a complex system regarding the definition of methodologies and data to utilize. Scale variability is both frequently, and at the same time, a cause and result of the techniques and methods that are developed.

Land use maps are the representation of a complex reality, with which we seek to identify objects and attribute meanings to the role of spatial units.

The increase in satellite spatial resolution and the detail thereby contained in an image have brought new contours to land use, both on a large scale and with further division of nomenclature to be utilized. However, automatic and/or semi-automatic classification still does not provide the desired detail, mainly in areas predominantly heterogeneous, as is the case with urban areas. This difficulty is linked not only to the geometric/spatial complexity of these areas but also to the semantic complexity of their physical entities - i.e. the identification of some classes of use does not depend so much on the physical characteristics of their objects, but on the functions attributed to them. Approaches adopted at the pixel level present their own difficulties, as they work above all in the area of the spectral response present in the image, when empirical differentiation of these same objects incorporates other elements inherent to the physical and social nature of the object.

Trying to resolve this problem, Remote sensing and GIS are ever more being used to develop useful sources of information[8,4]. But the urban environment, because of its heterogeneous and dynamic landscape, has been exigent to the applicability of these methods and technologies. Auspiciously, up to date innovations in data, technologies, and theories have provided scientists and users with helpful knowledge for the study of complex urban areas[14,23,38]. Moreover, classification approaches based on decision trees[7], evidential reasoning[29] and especially feedforward neural networks[1,13] have some promissory results. Neural networks are particularly appealing for supervised classification due to their non-parametric nature and ability to learn by example[30]. Furthermore, they have usually classified land cover more accurately than alternative approaches[1,27,28]. However, there are still problems and the applications usually don't make much better than 80% accuracy.

Thus, methods to enhance the classification procedure are required if land use/cover is to be mapped accurately. This paper aims to evaluate the potential to increase the land use/cover information derived from a object oriented neural network approach to image classification. Specifically it aims to show that by using spectral, textural and ancillary (statistic) data it is possible, over a vector base, to produce a classification that may appropriately represent land use/cover.

DATA AND METHODOLOGY

The study area, corresponding to a rectangle with 2.5 km height by 7 km width is located in the municipality of Almada (Figure 1), located in the south bank of Tagus River and corresponding to one of the core regions of the Lisbon Metropolitan Area (Portugal).

The satellite data used was a 2004 HRVIR SPOT image, with fusion between the panchromatic (supermode 2.5 meters) and the multispectral bands (10 meters) through a transformation between RGB-IHS-RGB color spaces, which allowed a final spatial resolution of 2.5 meters for all the bands.

Also ancillary data was used, such as the results of the Portuguese Population General Census statistics (2001), referenced to the subsection vector basis (equivalent to the UK enumeration district, known as GBIR) and the Municipal Master Plan (MMP).

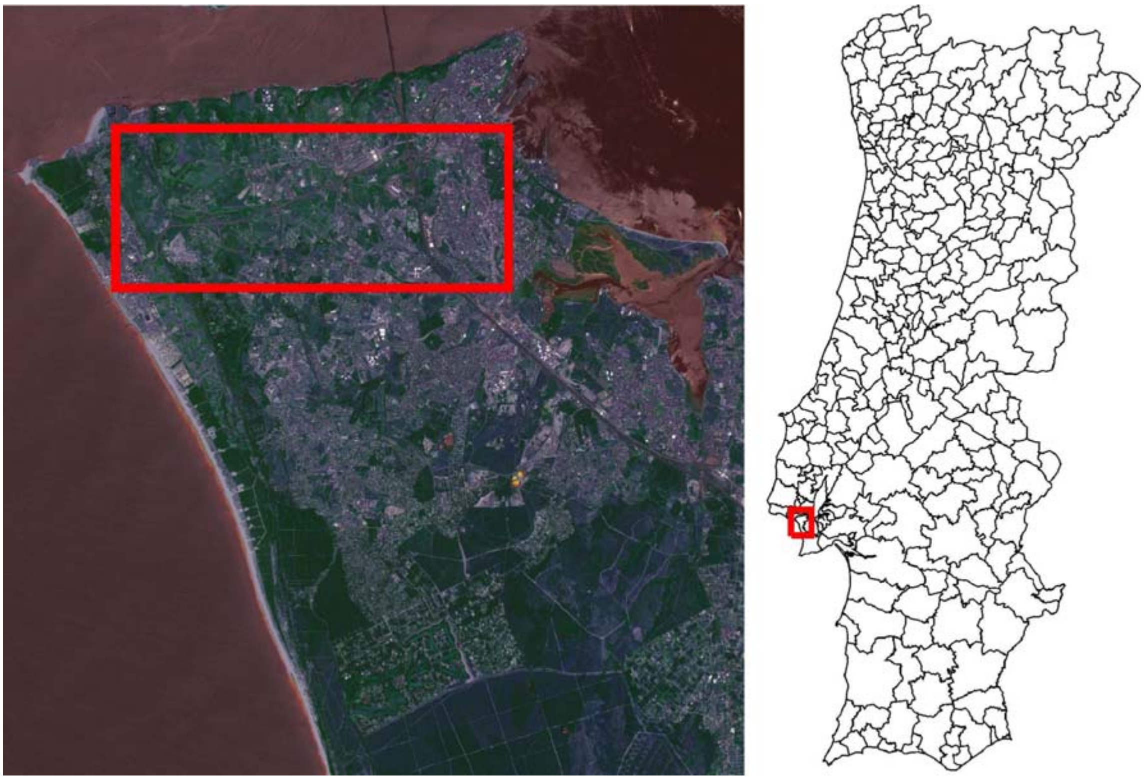

Fig. 1. Location of the test area.

The Portuguese Population General Census statistics comprises a large set of data, divided into four subgroups: “Families”, “Dwellings”, “Individuals” and “Buildings”. Taking into account the proposed methodology, a first selection of census data (Table 1) was made.

Table 1. First selection of statistical information.

FIELDS	**MEANING**
Number of familiar dwellings	All that have, at least, one family
Number of classical dwellings	All that belong to classical buildings
Number of collective dwellings	Hotels, hospitals, prisons
Number of present individuals	All the individuals that live in the subsection (whether they where present or not at the time of the inquire)
Number of classical buildings	Buildings built up with resistant material (for which a lifetime of at least 10 years is expected)
Buildings by construction date	Buildings by construction date
Buildings by number of floors	Buildings by number of floors
Exclusively residential buildings	Exclusively destined for residential purposes
Mainly residential buildings	Mainly destined for residential purposes
Mainly non residential buildings	Mainly destined for non residential purposes

In what concerns the Municipal Master Plan (MMP), although the represented classes are predominantly an indication of what is or not, allowed to construct in the future, some classes represent the existing land uses at the plan elaboration date. These were used in post-classification sorting rules, with the objective to improve the classification results.

The classification procedure is based on 5 main phases (Figure 2): (1) Legend creation; (2) acquisition of statistical auxiliary data proceeding from GBIR; (3) image multiresolution segmentation strategy for construction of different scales objects that have good similarity with the shape of the land use/cover final objects (polygons) and objects attributes acquisition, mainly, context, texture, spectral information, shape, among others; (4) deriving spectral data as class statistics and probabilities and (5) integration of the data different types in a neuronal network for classification and posterior discriminated analysis of the land use/cover spatial units (post-classification sorting).

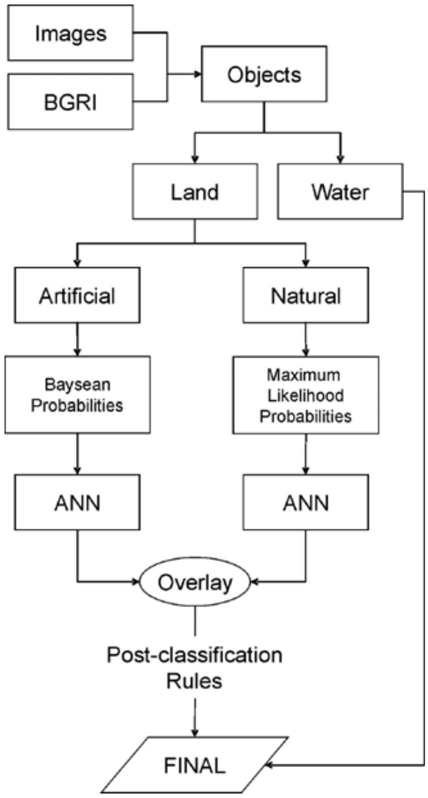

Fig. 2. Applied methodology schema.

CLASSIFICATION

The classification procedure is bases in five steps: 1) Legend creation; 2) deriving statistical ancillary data; 3) deriving object (texture) data; 4) deriving spectral data and 5) neural network classification.

Legend definition

The first step through the final classification as choosing the legend, requiring an analysis of different operational land use/land cover cartography projects/programs namely: at the national level: (1) CORINE Land Cover inventory, (2) the Portugal Land Cover Map (COS) e (3) a Lisbon Metropolitan Area land Use Map (CARTUS-AML); and at the international level – (4) the Murbandy/Moland project, and (5) the USGS- Land Use and Land Cover Classification.

Since the main goal was to classify the land use (and not the land cover), specially for the separation of high density and low density residential areas, at the end it was decided to adopt the legend of the Lisbon Metropolitan Area Land Use Map (CARTUS-AML). This map was produced at the 1:25000 scale, with 19 classes, for 1990 and updated for 1998. It was developed with stereoscopic visual analysis of panchromatic and infra-red vertical aerial photography and digital image processing of LANDSAT TM and SPOT XS and P, with incorporation of vector ancillary information.

This is not a hierarchy type of legend, although it contains land use units that show a strong approximation to the scale of analysis in local/regional planning, as the following classes shown in Table 2.

Table 2. Land Use/Cover classes.

ID#	Class
1	Agriculture
2	Bare Soil
3	Mining
4	Infrastructures
5	Shrubs
6	*Montado*
7	Ancient Urban Nucleus
8	Forest
9	Military Area
10	Harbors and Industry
11	Multi Family
12	Single Family
13	Urban Green Area
14	Commerce and Services
15	New Urbanizations
16	Water regions
17	Beach and Coastal areas
18	Marsh
19	Multifunction Metropolitan Area

Statistical ancillary data

Concerning the occurrence probabilities several considerations can be made: 1) buildings data contains information that can be efficiently correlated with reflectance (in contrast to what happens to the dwellings, that are "invisible" from satellite images); 2) buildings data provides the sufficient information for the ´a priori´ probabilities computation, for some of the urban classes, namely: ´Commerce and Services´, ´Ancient Urban Nucleus´, ´Multi-family Houses´, ´Single-family Houses´.

Once selected the Census indexes, it was necessary to establish formulas to calculate the occurrence probabilities of the four above-mentioned urban classes. The buildings exclusively or mainly destined for residential purposes, with more than two floors, have been considered as Multi-family Housing. The buildings exclusively or mainly destined for residential purposes, with one or two floors have been considered as Single-family Housing. The Ancient Urban Nucleus was established as the set of buildings constructed up to 1945, inclusively. In fact, in the 40´s occurred an alteration in the type of materials used in construction, fact that is also perceivable on the satellite images, which allows a significant correlation between the two types of data (spectral and statistical). The Commerce and Service buildings have been considered those buildings mainly destined for non-residential purposes, independently of the construction date or number of floors.

Let consider the following symbols, referred to a given sub-section:

MFB_t: number of multi-family buildings;

SFB_t: number of single-family buildings;

CS: number of buildings mainly destined for non residential purposes;

TB: total number of buildings;

MFB: number of multi-family buildings, constructed after 1945;

SFB: number of single-family buildings, constructed after 1945;

AUN: number of (exclusively or mainly) residential buildings, constructed before 1945.

The ´a priori´ occurrence probabilities will be given by:

$$p(\text{´Multi-family Houses´}) = p(MFB)=MFB/TB \quad (1)$$

$$p(\text{´Single-family Houses´}) = p(SFB)=SFB/TB \quad (2)$$

$$p(\text{´Ancient Urban Nucleus ´}) = p(AUN)=AUN/TB \quad (3)$$

$$p(\text{´Commerce and Services´}) = p(CS)=CS/TB \quad (4)$$

Of course, the four probabilities summation must equal one. Note however that some of the required indexes (namely MFB, SFB and AUN) are not directly available. For instance, we have the number of multi-family houses and the number of buildings constructed after 1945, but not the ´number of multi-family buildings, constructed after 1945´, as required. Taking these facts into account, the following strategy for the ´a priori´ probabilities computation was adopted:

Compute p(CS)=CS/TB

If p(CS)>0.8 then

p(CS)=1, p(MFB)=p(SFB)=p(AUN)=0

else

p(CS)=0

If p(CS)=0 then

p(AUN)=AUN/TE

p(MFB)=(MFB_t – α AUN)/TE

p(SFB)=(SHB_t – β AUN)/TE

The parameters α and β (α+β=1) accounts for the fraction of ancient buildings that are multi-family and single-family, respectively. In the experimental results we used α =β=0.5. All the statistical data (17 attributes) will be attached to the 570 polygons (objects) urban quarter vector base (Figure 3).

Fig. 3. Statistical vector base.

Object data

The image was segmented using eCognition 4.0. Here the objects are constructed through multi-resolution segmentation, a bottom-up region-merging technique. The objects will be filled in or not, in accordance with decision criteria, such as that of homogeneity and the scale parameter. The process seeks to minimize heterogeneity, by considering the size of the object. The scale parameter determines the continuation or cessation of the process. The general criterion of heterogeneity consists of two features, namely color and shape:

$$f = w + h_{color} + (1 - w) + h_{shape} \tag{5}$$

Variation in the scale parameter enables the creation of different levels of spatial perception, causing the dimension and shape of the object to vary. These levels result in a hierarchical object net-work, through which a particular object becomes aware of its neighbors and its sub and supra-objects. In order to create 2 levels of segmentation, the following set of parameters were chosen (Table 3). Level 1 was necessary to calculate some of the texture attributes of level 2 objects. Level 2 was then exported to be incorporated in the classification process. To the export image objects of level 2, were incorporated 14 attributes: 6 for spectral information, 3 for shape, 4 for texture and 1 for spatial context.

Table 3. Two levels segmentation parameters.

	Level 1	Level 2
Scale Parameter	10	15
Colour	0.1	0.1
Shape	0.9	0.9
Smoothness	0.5	0.5
Compactness	0.5	0.5
Image considered for the segmentation	Panchromatic	Multiresolution (4)

All object (13 547) related parameters are linked with a vector segmentation base (Figure 4). In this phase 14 attributes had been created, 6 for spectral information, 3 for shape, 4 for texture and 1 for spatial context.

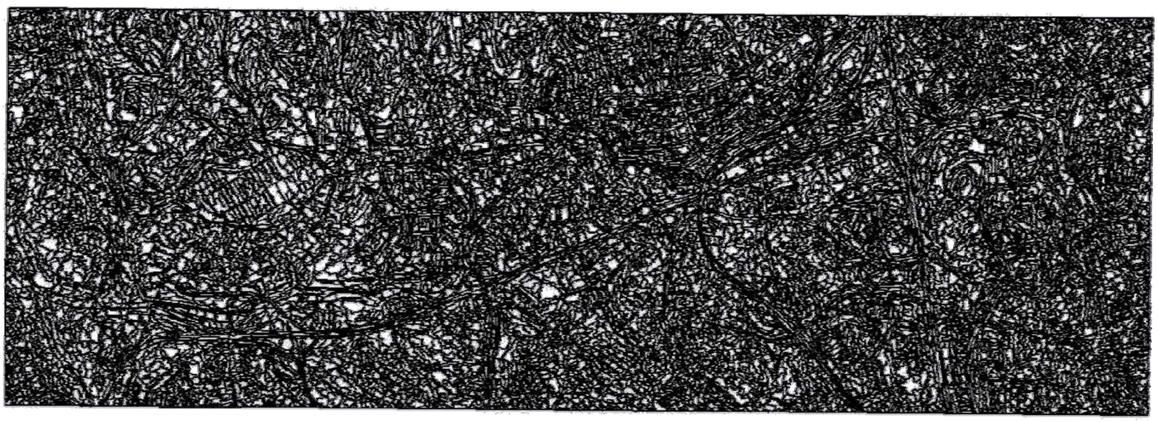

Fig. 4. Vector segmentation base.

Spectral data

The spectral data acquiring procedure consists in the application of a traditional ISODATA algorithm having, as inputs: the 5 spectral bands. The reason for choosing a ISODATA algorithm is related with the intention of not define land use/cover classes at this time. The best result (in terms of maximizing the discrimination) was achieved with 19 classes on the ISODATA algorithm.

As a result of this phase, a nineteen classes vector base with 98 302 objects was created, through an associated alphanumeric database comprising all the spectral characteristics of these classes (Figure 5). In the end there're 11 attributes for each spectral band, resulting in a total of 55 attributes.

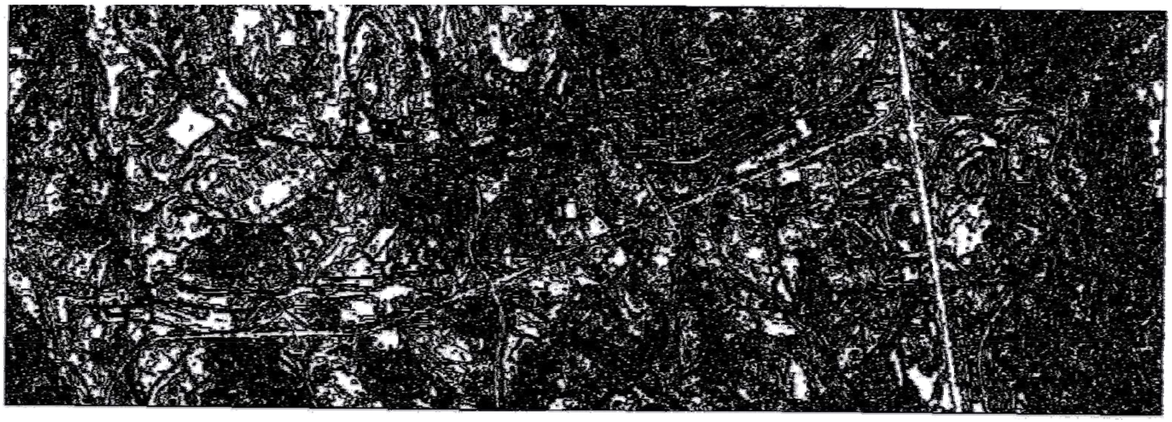

Fig. 5. The spectral classes vector base.

Finally all 3 vector bases are overlapped, creating a final base (Figure 6) with 243 474 objects and 86 attributes.

Fig. 6. The final vector classification base.

Object oriented neural network classification

For the classification itself, an Artificial Neural Network (ANN) was chosen, for a supervised imagery classification, dimensioning all data to the reference layer (Almada). Regarding the ANN structure, the option was for a multi-layer perceptron (MLP) incorporating a back-propagation train algorithm.

The MLP is organized in three layers: (i) one input layer; (ii) one or more hidden layers and (iii) one output layer. The number and dimension of the hidden layers is variable, but the architecture should be designed as simply as possible because the simulation has many loops. Some studies indicate that difficult learning tasks can be simplified by increasing the number of hidden layers, but a three layer network can form any decision boundaries, varying only the number of hidden neurons.

According to Kolmogorov's theorem, the use of 2n+1 hidden neurons can guarantee the perfect fit of any continuous functions and reducing the number of neurons may lead to lesser accuracy. However, in applications 2n+1 hidden neurons may be too many. A solution of 2n/3 hidden neurons can generate results of similar accuracy with much less training time. In this model, thirty hidden neurons in one hidden layer were used to ensure a balance between accuracy and simulation speed. The input layer comprises fifty neurons corresponding all the data produced by the merging of the statistical, object and spectral, vector databases; the output layer, defined by the number of expected classes in the processing, integrates nineteen classes from CARTUS-AML.

Post-classification sorting

The last stage of the classification procedure re-classifies pixels attributed to the wrong classes in the previous steps, through the application of contextual rules and the use of information directly available from the ancillary data.

For the area on study, four different classes of use are considered in this step: ´Harbors and Industry´ and ‘Infrastructures´. These classes results from the information available in the MMP:

´ Harbors and Industry ´ - pixels classified in urban classes, but signalized as existing ´industry´ in the MMP;

´Infrastructures´- pixels classified in urban classes, but signalized as existing ´Infrastructures´ in the MMP;

RESULTS AND CONCLUSIONS

From the classification results (Figure 7) some considerations could be drawn:

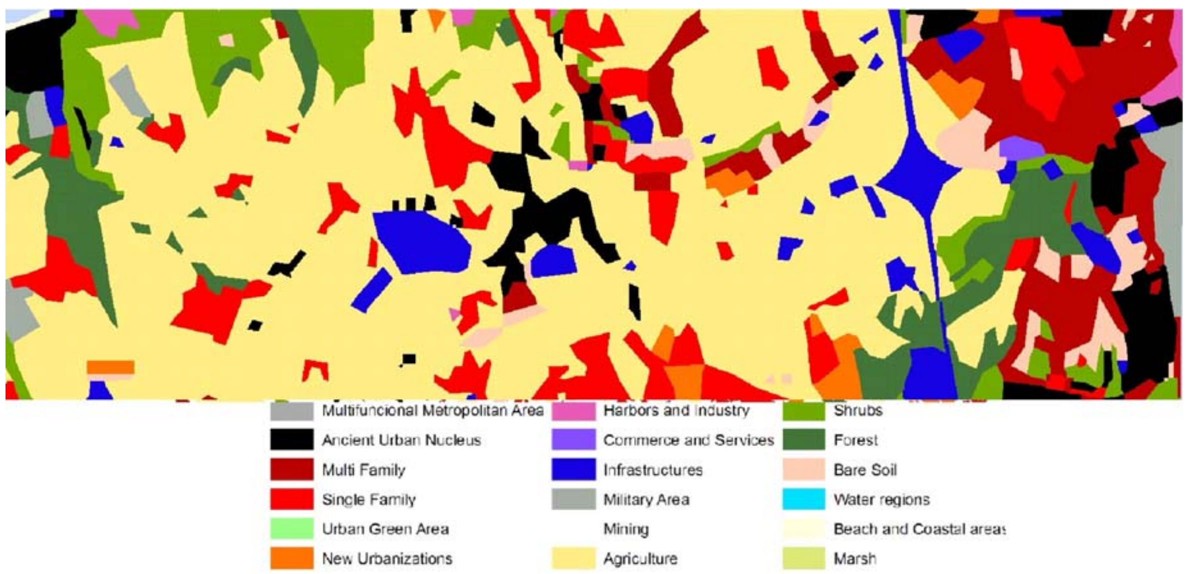

Fig. 7. Classification map.

The proposed method achieved (89%), in a global perspective, better results than the traditional ones as we can achieved with traditional classifiers (74% for ML).

In a more detailed analysis, it is possible to see that the proposed method gets a better accuracy for all classes.

The proposed method has improved the overall accuracy (higher than 97 %) of the classes where was a direct use of statistical information.

The classifier failed in part the analysis of roads (60 %, but the problem can be minimized using specific post-classification rules for this class). Thus, the problem that affects roads also appears in the other classes: the accuracy is higher in the polygons centre and declines through the boundary direction.

The proposed method allows the identification of classes (e.g., ´Commerce and Services´), "invisible" on the satellite images.

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