

Land use/cover classification using orbital and ancillary data, neural networks and multiresolution segmentation

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ABSTRACT: In this paper, a land use/cover classification methodology of the rural/urban fringe is presented, 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 (to assist). 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 developed procedure is based on 4 phases: (i) 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); (ii) objects attributes acquisition, mainly, context, texture, spectral information, shape, among others; (iii) acquisition of statistical auxiliary data proceeding from the Geographic Base of Information Referencing (BGRI in Portuguese); (iv) integration of the data different types in a neuronal network for classification and posterior discriminated analysis of the land use/cover spatial units.

Data used in this methodological experimentation 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. This resolution was respected in the images gathered from the alphanumeric database associated to the BGRI.

1 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 do(es) 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.

2 METHODS

The study area is 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

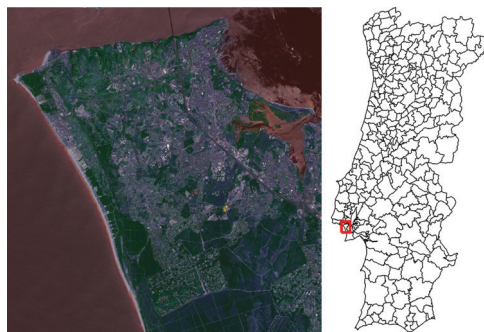


Figure 1. Almada Municipality Location and a colour composite image (RGB214) of the area.

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 BGRI) and the Municipal Master Plan (MMP).

The classification procedure is based on 4 phases (Figure 2): (1) image multi-resolution segmentation strategy for construction of different scales objects that have good similarity with the shape of the land use/cover final objects (polygons); (2) objects attributes acquisition, mainly, context, texture, spectral information, shape, among

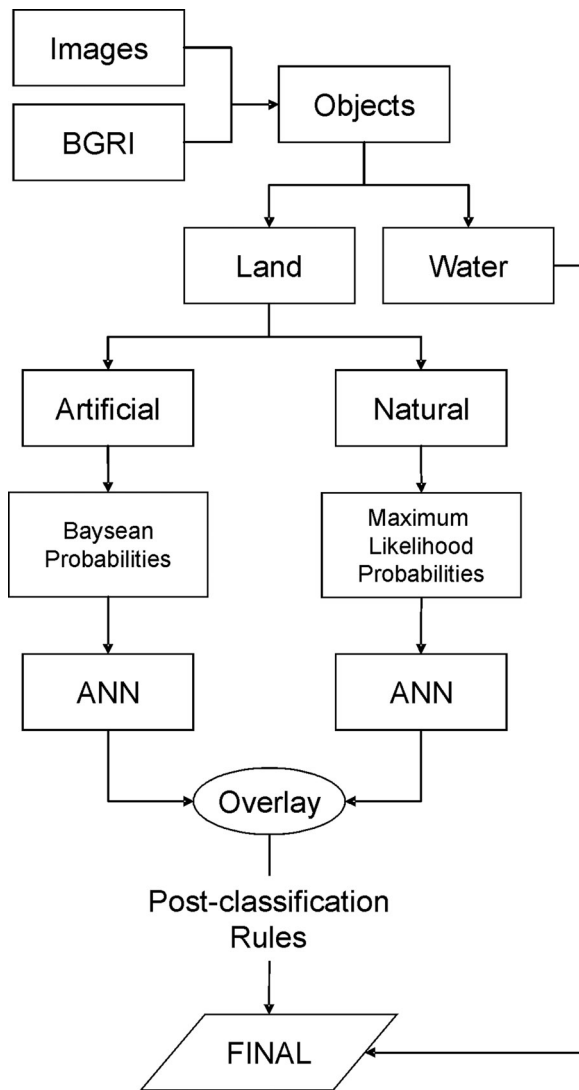


Figure 2. Applied methodology schema.

others; (3) acquisition of statistical auxiliary data proceeding from BGRI in Portuguese; (4) 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).

3 CLASSIFICATION

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 auxiliary information (i).

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 1:

Table 1. Land use/cover classes.

ID#	Class
1	Agriculture
2	Bare Soil
3	Mining
4	Infrastructures
5	Shrubs
6	<i>Montado</i>
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

3.1 Objects creation

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 colour and shape:

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

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 network, through which a particular object becomes aware of its neighbors and its sub and supra -objects (ii). In order to create 2 levels of segmentation, the following set of parameters were chosen (Table 2). 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.

In the end of this procedure the objects achieved through image analysis (~112000) had been merged with BGRI, creating a new object database, now with 120000 objects (Figure 3).

3.2 Objects classification

The first objective of this stage is to have, at the classifier input, three main stratum – “water”, “urban areas”, “non-urban areas” – that will be processed individually. Then, the natural uses occurrence probabilities, were extracted using a Maximum-likelihood (ML) classifier. The artificial classes occurrence probabilities constitute the base for the Bayesian classifier application. These probabilities allow discriminating four urban classes (‘Commerce and Services’, ‘Ancient Urban Nucleus’) that, due to their similar spectral responses, would be misclassified if a ML classifier were applied.

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

Table 2. Two levels segmentation parameters.

	Level 1	Level 2
Scale Parameter	10	15
Color	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)

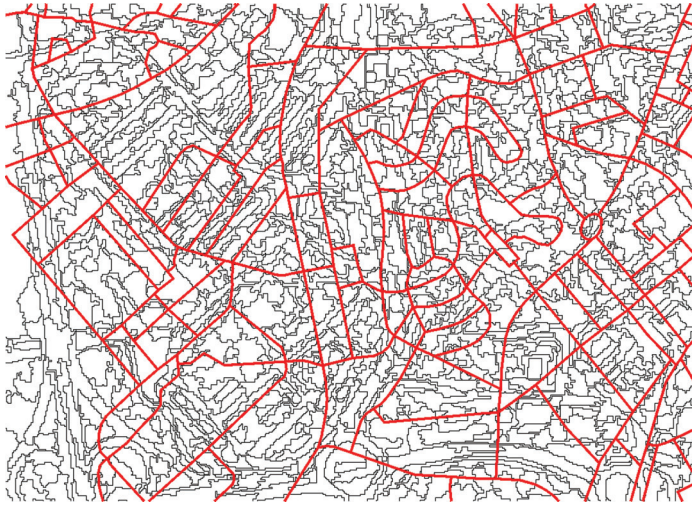


Figure 3. Final object database.

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:

$$p(\text{‘Multi-family Houses’}) \equiv p(\text{MFB}) = \text{MFB}/\text{TB}$$

$$p(\text{‘Single-family Houses’}) \equiv p(\text{SFB}) = \text{SFB}/\text{TB}$$

$$p(\text{'Ancient Urban Nucleus'}) \equiv p(\text{AUN}) = \text{AUN}/\text{TB}$$

$$p(\text{'Commerce and Services'}) \equiv p(\text{CS}) = \text{CS}/\text{TB}$$

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:

$$\text{Compute } p(\text{CS}) = \text{CS}/\text{TB}$$

$$\text{If } p(\text{CS}) > 0.8 \text{ then}$$

$$p(\text{CS}) = 1, p(\text{MFB}) = p(\text{SFB}) = p(\text{AUN}) = 0$$

$$\text{else}$$

$$p(\text{CS}) = 0$$

$$\text{If } p(\text{CS}) = 0 \text{ then}$$

$$p(\text{AUN}) = \text{AUN}/\text{TE}$$

$$p(\text{MFB}) = (\text{MFB}_t - \alpha \text{AUN})/\text{TE}$$

$$p(\text{SFB}) = (\text{SHB}_t - \beta \text{AUN})/\text{TE}$$

The parameters α and β ($\alpha + \beta = 1$) accounts for the fraction of ancient buildings that are multi-family and single-family, respectively. In the experimental results we used $\alpha = \beta = 0.5$.

For the classification itself, an Artificial Neural Network (ANN) was chosen, for a supervised imagery classification, dimensioning all data to the reference layer (Almada). For ANN it is more appropriate that input data have a [0, 1] range, that was done in the previous phase of data normalization. Regarding the ANN structure, the option was for a multi-layer perceptron (MLP) incorporating a back-propagation train algorithm.

The MLP is organised 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, twelve hidden neurons in one hidden layer were used to ensure a balance between accuracy and simulation speed. The input layer comprises five neurons corresponding to 5 bands of SPOT5 (HRVIR-1, HRVIR-2, HRVIR-3, HRVIR-4 and Panchromatic); the output layer, defined by the number of expected classes in the processing, integrates nineteen classes from CARTUS-AML.

3.3 *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: ‘Roads’, ‘Beach’, ‘Industry’ and ‘Sports Equipment’ (a sub-class of the ‘equipment’), like football fields and tennis courts. The ‘roads’ class is directly available from the Road Network. The remaining classes results from the information available in the MMP or, for the missing cases, from the following contextual rules:

‘Beach’ – pixels that, although belonging to the urban areas (value ‘1’ in the urb_2 mask), were not classified in any of the urban classes and at a geographical position not far from 200 m of the line coast;

‘Industry’ – pixels classified in urban classes (value ‘1’ in the urb_fin mask), but signalised as ‘industry’ in the MMP;

‘Sports Equipment’ – pixels classified as ‘Shrubs’ or ‘Bare soil’, comprising a region with an area and perimeter typical of football fields or tennis courts, and at a geographical position not far from 500 m of a road.

All the extracted classes are then integrated in the final classification map, according to the following algorithm:

The replenishment of the final map is performed from the highest to the lowest confidence classes, namely:

‘Commerce and Services’; ‘Ancient Urban Nucleus’ (obtained from the Bayes classifier)

‘Sports Equipments’; ‘Beach’ (resulting from the MMP and/or contextual rules)

‘Industry’ (resulting from MMP)

Other urban and non-urban classes (resulting, respectively, from the Bayes and ML classifiers)

Once a label (class) has been attributed to a pixel, it cannot be overwritten by another label.

4 CONCLUSIONS

From the classification results (Figure 4) some considerations could be drawn:

The proposed method achieved (89%), in a global perspective, better results than the traditional ones as we can achieve 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.

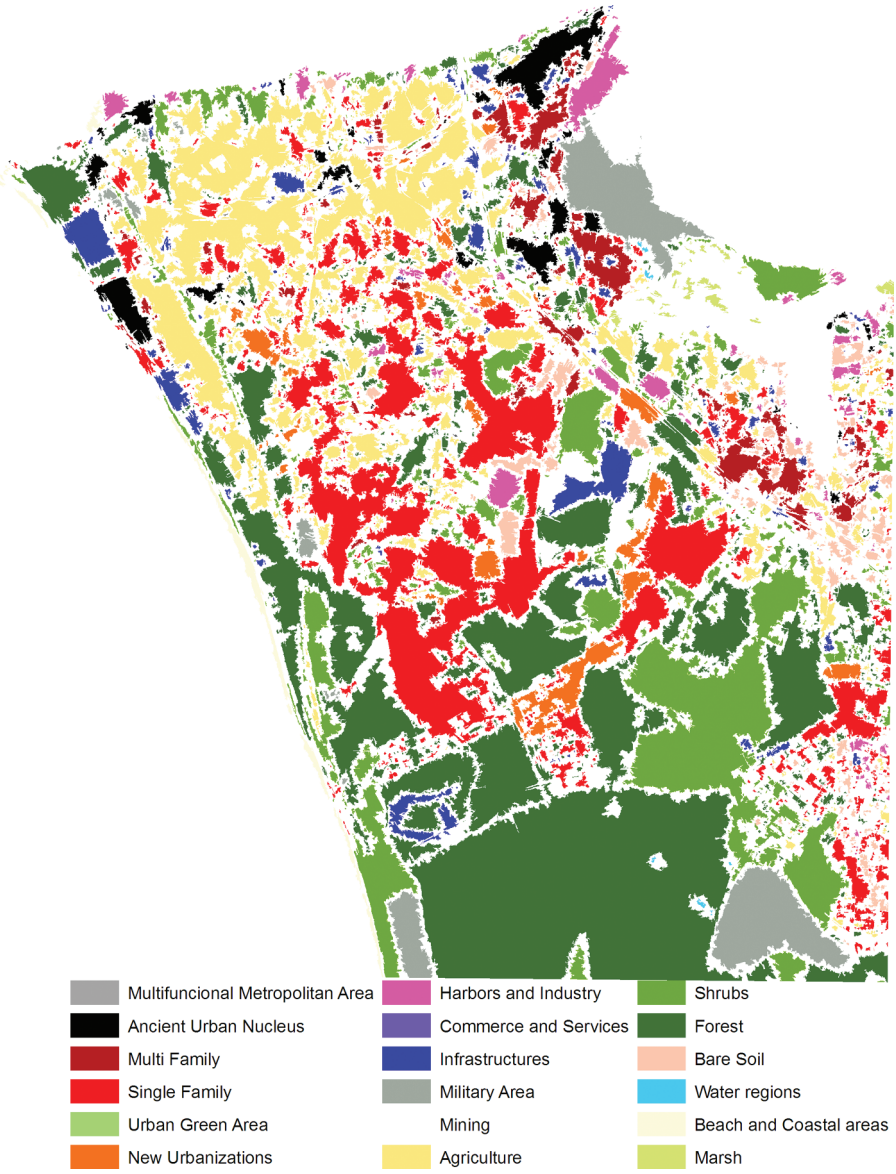


Figure 4. Objects (polygons) classified with 100% accuracy.

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