METHODS FOR AUTOMATIC EXTRACTION OF REGULARITY PATTERNS AND ITS APPLICATION TO OBJECT-ORIENTED IMAGE CLASSIFICATION

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ABSTRACT:

Detection and quantification of regularity patterns are important structural aspects for object-oriented classification of images for geo-databases updating. Four image processing methods are analysed and evaluated for this purpose: semivariogram analysis, the Hough transform, the histogram of minimum distances, and Fourier space descriptors. In addition, several features are extracted from each method and evaluated for classification of regular and non regular parcels in a rural environment. The classification has been performed by using the C5 algorithm, based on data mining techniques. A total of 276 objects have been evaluated using the cross-validation method. After selecting the most discriminant features, a land use object-oriented classification has been performed, which includes some spectral and textural features in the model. The results show that the features based on the semivariogram and the Hough transform are the most efficient for detecting regularity patterns. The combination of the three groups of features (spectral, textural and structural) clearly improves the classification of parcels, which is encouraging for automated land use cartography updating.

1. INTRODUCTION

A strategic issue brought on by the evolution of the geoinformation systems is the application and development of new methods that allow for an efficient generation and update of geographic databases by means of integrating different types of data. In this sense, aerial and high resolution satellite images play an important role, since they can be acquired with a high frequency, they offer a variety of spectral information - including infrared bands- and the image processing methods are evolving and being improved in order to automate some tasks that have traditionally been done by interpretation and field work.

Usually, classification techniques are applied for updating cartographic databases from images, and very often object-oriented classification methods are used to avoid errors related to the borders of landscape elements. This means that each object is classified independently, from different features that are extracted in a specific manner. The limits of the objects can be defined by image segmentation, using cadastral units or other existing georeferenced databases, which changes the traditional *per-pixel* approaches based on *one pixel-one value*.

In the characterisation of objects in the image, different types of features can be used, such as spectral, textural, and/or structural. The first are directly based on the values of the spectral bands, or on indices or combinations derived from them. Textural features attempt to describe the spatial relationships of the data values within an object; and the structural features provide information about specific patterns or arrangements of landscape elements contained in the object. These are more related to the way in which the humans interpret and understand the scenes. In this context, a relevant property that helps us to describe the landscape is the presence, degree and type of regularity patterns that provide the final configuration of an object. Therefore, the definition of variables or features extracted from images that give us a quantification of the regularity patterns is important to improve the automatic classification of objects, with the final aim of increasing the efficiency of the processes to update land cover information systems.

The objectives pursued in this work are the development and extraction from images of quantitative parameters or indicators that allow for the identification of regularity in agricultural objects (e.g. cadastral units, parcels, etc.), the evaluation of these parameters and the selection according to their efficiency for the classification of the objects. An application of the methods is performed using aerial images from a rural environment in the Mediterranean area of Spain.

2. PRE-PROCESSING OF DATA

The data used for this study were 0.5 meters resolution digital aerial orthoimages acquired in August 2005 using the DMC (*Digital Mapping Camera*). This is a CCD sensor with three bands in the visible part of the electromagnetic spectrum (0.4-0.58 µm, 0.50-0.65 µm, and 0.59-0.675 µm), one in the NIR (0.675-0.85 µm) and a panchromatic band. In addition, the definition of the objects to classify was based on the vectorial limits obtained from regular cadastral units or parcels from the area of *Castellón*, on the Mediterranean coast of Spain. A set of 276 rural parcels was selected for the test, representing different types of land use/land cover, such as *Citrus* orchards, other crops, forest, shrub, fallow and barren soil. Since the principal aim was to detect the presence of regular patterns, all the objects were pre-classified as regular or non regular, maintaining a balanced proportion of both types.

With the exception of the feature extraction method based on the analysis of the semivariogram, the other three methods proposed use pre-processed binary images in which the position of trees has been estimated. This is because the principal factor of regularity in rural landscapes is due to the relative position of the trees in the terrain. The location of the trees inside an object is based on the *local maximum filtering* method (Pouliot, 2002; Nelson, 2005; Wulder, 2000), which is based on the assumption that reflectance is highest at the tree apex and decreases towards the crown edge (Wulder, 2000). Moving a kernel over the image, trees are found when the central value in the kernel window is higher than all other values. The scene illumination has an important influence on local maxima position, displacing their position from the real apex location. This displacement has not factual effects because it equally affects to all the maxima located.

In this study, since most of regular features present in the images used were due to different crop arrangements, a local maximum method was applied over NDVI images using a circular kernel with variable diameter size, ranging from 9 pixels to 23 pixels. The size of this circular neighbourhood was determined as the position of the first maximum value of the semivariogram curve, which is computed for each particular object. This position is in accordance with the mean tree separation in the parcel, ensuring that a tree, but no more than one, is present inside the window, assuming a regular distribution of the trees in the parcel. Additionally, a minimum threshold was defined in order to avoid the selection of maximum points in non-vegetated areas. In those parcels with a low NDVI mean value, the tree search consists of local minimum finding over the NIR band. This variation is applied to locate young trees recently planted. The result is a binary image, where each located tree is represented by a pixel (see examples in figures 2 and 3).

3. METHODS FOR EXTRACTION OF INDICATORS OF REGULARITY PATTERNS

Four methods were used to extract regularity indicators: Analysis of the semivariogram, the Hough transform, the histogram of minimum distances between trees, and Fourier space descriptors. The first uses the red band as input, while the last three use the binary image containing the estimated position of trees as input data.

3.1 Analysis of the Semivariogram

The semivariogram quantifies the spatial associations of the values of a variable, and measures the degree of spatial correlation between different pixels in an image. The experimental semivariogram is defined as:

$$\gamma(h) = \frac{1}{2N}\sum_{i=1}^{N}\left[Z(x_i) - Z(x_i + h)\right]^2$$

where $Z(x_i)$ represents the gray level for a generic pixel in the location x_i; N is the number of pixels considered; and h is a vector that represents the distance between pixels in a particular direction. Several authors have used information extracted from the semivariogram to incorporate texture into image classification (Miranda et al., 1998; Carr and Miranda, 1998; Chica-Olmo and Abarca, 2000; Maillard, 2003; Durrieu et al., 2005).

One object-specific semivariogram was computed for every parcel. Figure 1 shows some examples of curves associated with different types of land use, and their relationship with the regularity of the landscape elements. Several parameters were measured to extract a set of features: the position of the first maximum and its value, the slope between the first maximum and the fist minimum, and the slope between the first minimum and the second maximum. In addition, other parameters were used as reported by Durrieu et al. (2005).

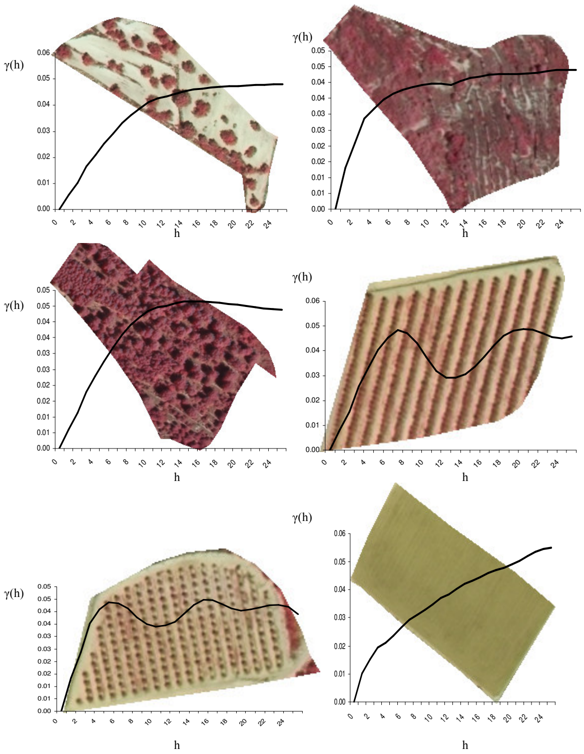


Figure 1.- Examples of six parcels with different use, and their respective experimental semivariogram *γ(h)* superimposed.

3.2 The Hough Transform

This method is based on the transformation of the coordinates of points from a cartesian image space (*X,Y*) to a polar coordinate space (*ρ, θ*), where *ρ* represents the distance from the origin to a point, and *θ* its angle with respect to the *X* axis. The points in cartesian space correspond to sinusoids in polar space, and a line in this space is defined by a point where several sinusoids are intersected (figure 2).

The histogram of angular values ranging from 0º to 180º is computed, the two maxima corresponding to the principal directions or alignments of trees in the parcels when some regularity in their spatial arrangement exists (figure 2). A total of 15 parameters related to the regularity of the distribution of trees were defined based on this transformation and the histogram of orientations. Some of them, selected upon the criteria described in section 4, are specified in table 1.

In addition to the variables for classification, this method allows for the determination of the distance between trees, following the two principal directions (see detail in figure 3). This information can be useful for inventories, as well as to discriminate different species of agricultural trees (e.g., *Citrus*, olive trees, etc.).

3.3 Histogram of distances

This method consists of the computation of all distances among points extracted after the application of the local maxima method, and the selection of the minimum distance for each point. Then, a histogram of all the minimum distances is created for each parcel. The mean of this histogram provides information about the average separation of the elements, while its standard deviation gives information about the presence of regularity in the distribution. If the standard deviation is high, the points are expected to be randomly distributed, but if it is low, it means that the points are located at a similar distance from each other, inferring some regularity pattern. The skewness and kurtosis of the distribution were also initially considered, but they did not show any relevance after the evaluation.

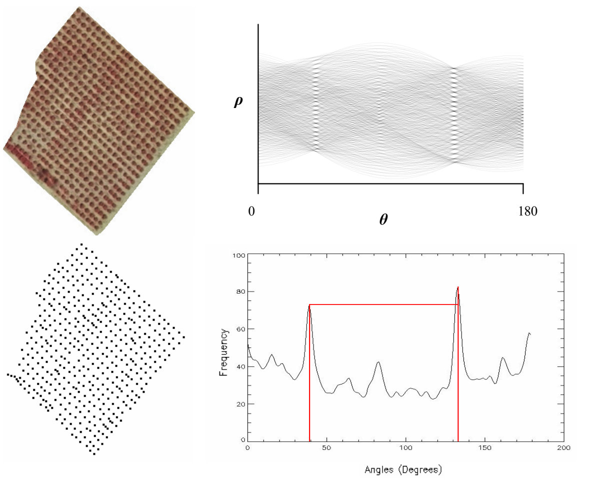


Figure 2.- First column: A parcel of *Citrus* trees (above) and their location after the application of the local maxima method (below). 2nd column: Representation of points on the space defined by Hough coordinates θ and ρ, and the histogram of the orientations (θ), with the two principal directions enhanced.

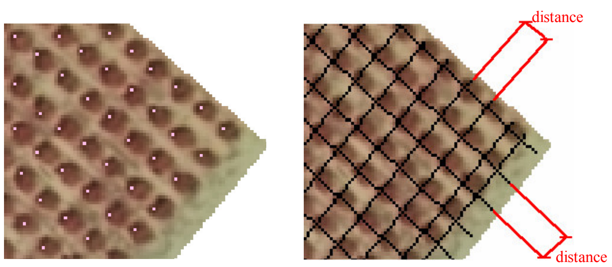


Figure 3.- Detail of identification of tree positions (left); extraction of the 2 principal directions of tree alignnment and the regular distance between trees (right).

3.4 Fourier Space Descriptors

After the application of the 2D Fourier transformation of an image, the Fourier spectrum reveals the existence of regular patterns in an organised manner. Based on the concept of the descriptors proposed by Gonzalez and Woods (1993), the regularity parameters have been extracted as follows: First, the direction of the maximum value of $S(\theta)$ is obtained, being

$$S(\theta) = \sum_{r=1}^{R} S_r(\theta)$$

where r is the radius from the origin of the frequency space and θ is the angle of the direction with respect to the X axis, which ranges from 0º to 180º. Once θ_{max} is obtained, a profile of the Fourier spectrum values is defined starting at the origin and following that direction (figure 4, left). Then the local maxima values of $S_{\theta_{\max}}(r)$ are computed (figure 4, right), representing the frequencies at which the main regular patterns occur.

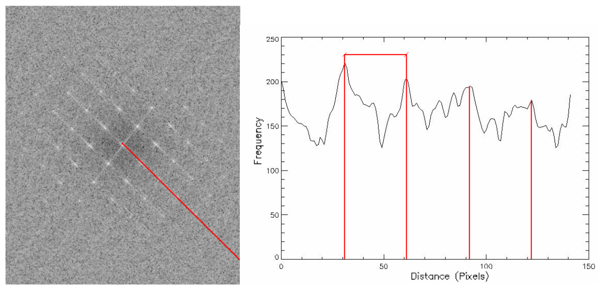


Figure 4.- Fourier spectrum of the image from figure 2 (left) and the profile of the direction $S_{\theta_{\max}}(r)$ of maximum change,.

The extraction of the maxima of these positions and the standard deviations of the differences among them in the frequency domain, provides a valuable information about the existence of regularity patterns in the images, being these the features extracted (table 1).

4. SELECTION OF VARIABLES AND CLASSIFICATION

4.1 Pre-selection of Variables by multivariate analysis

In the case of the methods based on the Hough transform and the semivariogram analysis, a high degree of redundancy existed in the total number of features extracted initially. Therefore, a statistical selection based on the stepwise discriminant analysis was applied over these two methods in particular. This was done in order to select a reduced number of features containing the most significant information relative to the regularity patterns in the objects.

The results of this selection process, in which all 276 parcels were used, are shown in the graph of figure 5. The overall accuracy obtained in the classification of regular and non regular patterns is represented for each of the four methods tested, as a function of the successive increase in the number of variables included in the classification model.

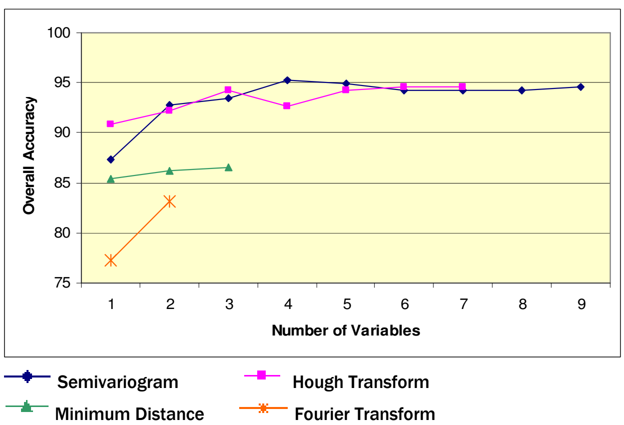


Figure 5.- Overall accuracy in the classification of regular/non regular parcels obtained using the four different sets of structural features tested.

By using the methods based on the semivariogram and the Hough transform, the selection of 4 or 5 variables is sufficient to obtain approximately 95% accuracy, while the methods based on the Fourier transform and in the minimum distance are less efficient, with an accuracy of about 85%, but using only 2 and 3 variables, respectively. Considering these results obtained by the discriminant analysis method, a combined set of 14 variables was selected from the initial set of features. These variables are described in the table 1.

Semivariogram Variables
Slope of the normalized semivariogram between the first maximum and the first minimum
Slope of the normalized semivariogram between the first minimum and the second maximum
$Smp3 = 1 - \left(\frac{\gamma(h_{max_2})}{\gamma(h_{max_1})} \right)$ Decay/increase of the semivariogram cycle*
Position of the first maximum
$Gp5 = \frac{\gamma(h_3) - 2\gamma(h_2) + \gamma(h_1)}{2h^2}$ Concavity/Convexity value at h_2 (variability in short distances)*
Hough Transform Variables
Proportion of points included in the principal direction with respect to the total points
Angular difference between the principal directions
Standard deviation of distances between points included in the principal direction
Proportion of points on the secondary direction with respect to the total aligned points
Minimum Distance Variables
Maximum frequency of the minimum distance between points normalized by the total area
Skewness of the distribution of minimum distances
Kurtosis of the distribution of minimum distances
Fourier Transform Variables
Normalized mean of the maxima detected in the direction of maximum change
Standard deviation of the distances between maxima in the same direction

(*) *From Durrieu et al., 2005.*

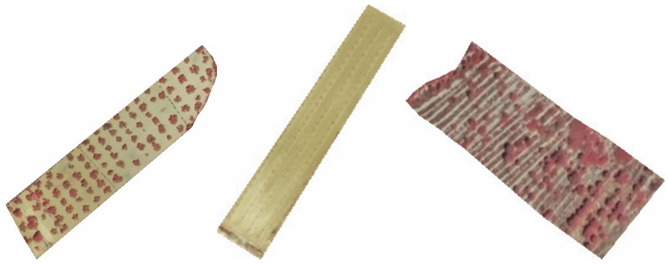
Table 1.- Group of variables describing regularity pre-selected after the application of the stepwise discriminant analysis method.

4.2 Decision tree binary classification

A decision tree is a set of conditions organized in hierarchical structure in such a way that the assignation of a class to an object can be determined following the conditions fulfilled by the object. The goal is to learn how to classify objects by analyzing a set of training samples whose classes are known. Classes are mutually exclusive labels. The objects are represented as vectors that give the numerical values of a collection of properties or features. Learning input consists of a set of such vectors, each belonging to a known class, and the output consists of a mapping from attribute values to classes.

A decision tree can be constructed from a set of rules by a *divide and conquer* strategy. A test with mutually exclusive outcomes is used to partition the training set into subsets that are more homogeneous than the initial set. For each potential test, the impurity degree of the generated subsets is calculated, and the test which generates the most homogeneous subsets is selected. The algorithm iterates until the subset elements belong to the same class. The algorithm employed is known as C5 and its splitting criterion is the *gain ratio*. The gain ratio criterion (Quinlan, 1996) assesses the desirability of a test as the ratio of its information gain to its split information, and the split with maximum gain ratio is selected.

A binary classification (regular/non regular) was made by means of the C5 algorithm and using the 14 selected features previously described. From the 276 parcels tested, only 6 were misclassified: 4 regular were classified as non regular, and 2 non regular as regular. Examples of these errors are shown in figure 6. Usually, the errors are due to the presence of unclear regular patterns (case of parcel *b*, containing very small aligned trees), or the presence of pseudo-patterns (case of parcel *c*, with terraces).



a) b) c)

Figure 6.- Examples of misclassification of objects with the decision-tree using the selected structural features. a) and b) regular objects classified as non regular. c) Non regular objects classified as regular.

These results show that the set of proposed features contains fundamental information about the distribution of patterns in images, allowing for the discrimination of regular and non regular parcels. In order to go further in the process of automated classification, another test was made including these structural features in a land use object-oriented classification process, as described in the next paragraph.

5. APPLICATION TO OBJECT-ORIENTED LAND USE CLASSIFICATION

An important application based on the use of structural information extracted from images is the automated classification of images for updating land use databases. Using the same set of cadastral parcels, an object-oriented classification of land use in a rural environment was made, considering the following 5 classes: *Citrus* orchards, Olive and/or carob trees (*Ceratonia siliqua*), Bare soil, Forest, and Shrub. In addition to the 14 structural features selected (table 1), 6 spectral features and 9 texture features were used as initial variables for the generation of the decision tree. The spectral features used were: the mean values of the NIR and red bands, and their standard deviations, as well as the mean NDVI and its standard deviation. The texture features used were based on the first order histogram (skewness and kurtosis), some of the texture features proposed by Haralick et al. (1973), that are extracted from the grey level co-occurrence matrix (uniformity, entropy, contrast, correlation and inverse difference moment), and the mean and standard deviation of the *edgeness* parameter. A complete description of the texture variables, as well as the selection process applied, is reported by Ruiz et al. (2004). The combination of these three groups of features and their object-oriented extraction is analysed by Recio et al. (2006).

The decision tree was generated by the C5 algorithm, using the described set of variables and the 5 classes described. The evaluation was performed using the cross-validation method, dividing the 276 objects into 10 equally sized sets, and repeating the same process ten times. Each time, 9 sets were used as training samples to compute the decision tree, and the other set was used for testing purposes. The results are shown in table 2. The overall accuracy was 89.9%, which means that the global information extracted from the images seems to be very efficient for the automated classification of such landscapes.

	Olive & Carob tree	*Citrus* orchards	Bare soil	Forest	Shrub	Total
Olive & Carob tree	56				5	61
Citrus orchards		104	5			109
Bare soil		2	25			27
Forest		1		27	5	33
Shrub	3	1		6	36	46
Total	59	108	30	33	46	276

Table 2.- Error matrix of the object-oriented classification of 5 different types of rural parcels using spectral, textural and structural features. Columns represent classified values and rows reference values. (Overall accuracy: 89.9%)

Some errors were due to the presence of very young orange trees (see example in figure 6b), that were confused with bare soil. In some cases, olive trees without a regular arrangement were classified as shrub. Another type of error was due to the difficulty in distinguishing between shrub and forest that sometimes occurs in the photointerpretation of the images. In general, it seems that most of the errors were produced in parcels where the visual interpretation of the type of cover has a high degree of difficulty.

6. CONCLUSIONS

An exhaustive set of structural features for the analysis of regularity of image objects, based on four different approaches, has been proposed. After the statistical selection of the most relevant features from the set, those extracted from the experimental semivariogram of each object, and those based on the Hough transform resulted to be particularly efficient for the discrimination of parcels containing elements with a regular spatial distribution pattern, usually due to the linear arrangement of trees in agricultural fields. Using a decision tree classification method based on the C5 algorithm, the final rate of error was only 2.2%, which shows that the regularity can be efficiently characterised using these image processing methods.

The results are particularly interesting for the application in automated land use object-oriented classification of images. In this sense, a test has been performed for the classification of aerial image objects defined by cadastral units, including spectral, texture and structural features extracted from the images. The overall accuracy obtained for a problem of 5 classes is of 89.9%, which is encouraging for the use of these techniques in more complex problems.

Finally, the application of object-oriented classification using a combination of complementary variables is a promising method in order to advance in the incorporation and standardisation of automated methods for updating geo-databases and map production.

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