A FEATURE EXTRACTION SOFTWARE TOOL FOR AGRICULTURAL OBJECT-BASED IMAGE ANALYSIS

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ABSTRACT

A software application for automatic descriptive feature extraction from image-objects, FETEX 2.0, is presented and described in this paper. The input data include a multispectral high resolution digital image and a vector file in shapefile format containing the polygons or objects, usually extracted from a geospatial database. The design of the available descriptive features or attributes has been mainly focused on the description of agricultural parcels, providing a variety of information: spectral information from the different image bands; textural descriptors of the distribution of the intensity values based on the grey level co-occurrence matrix, the wavelet transform and a factor of edgeness; structural features describing the spatial arrangement of the elements inside the objects, based on the semivariogram curve and the Hough transform; and several descriptors of the object shape. The output file is a table that can be produced in four alternative formats, containing a vector of features for every object processed. This table of numeric values describing the objects from different points of view can be externally used as input data for any classification software. Additionally, several types of graphs and images describing the feature extraction procedure are produced, useful for interpretation and understanding the process. A test of the processing times is included, as well as an application of the program in a real parcel-based classification problem, providing some results and analyzing the applicability, the future improvement of the methodologies, and the use of additional types of data sets. This software is intended to be a dynamic tool, integrating further data and feature extraction algorithms for the progressive improvement of land use/land cover database classification and agricultural database updating processes.

Keywords: feature extraction, parcel-based, image analysis, remote sensing, agricultural database updating, semivariogram, Hough transform, texture.

1.- INTRODUCTION

Image classification techniques are frequently used in remote sensing to face a wide range of applications, being traditionally focused on the analysis of independent pixels using multiple spectral bands as input data, sometimes introducing additional information related to the spatial distribution of the intensity values of the neighbourhood of the pixels, such as the case of the texture based approaches. Much attention has been paid to the process of creating the appropriate decision functions that optimize the accuracy results, and many different methodologies for the classification itself have been tested. However, a crucial step to be taken before the classification is the synthesis of the information or attributes that describe the image element to be classified. This is usually called the feature extraction process, and much less effort has been made in this sense, mainly because the classification has been fundamentally pixel-based, and not object-based, thus restricting the options used to enrich the set of features used as input for the classifiers.

Geographic Object-Based Image Analysis (GEOBIA) has been defined as a sub-discipline of *Geographic Information Science* devoted to partitioning remote sensing imagery into meaningful image-objects, and assessing their characteristics through spatial, spectral and temporal scale (Hay and Castilla, 2006). Before carrying out feature extraction and classification steps, these techniques require image segmentation. Segmentation refers to the process of partitioning a digital image into multiple segments, called image-objects or simply objects, in order to simplify and/or change the representation of an image into a more meaningful and homogeneous structure that is easier to analyze (Shapiro and Stockman, 2001). These segments have additional spectral and spatial information when compared with single pixels (Blaschke, 2010). Segmentation is the main problem of this analysis of the image because it has multiple solutions (Hay and Castilla, 2006; Zhang et al., 2008). Depending on the method and the parameters used, the results, that are the objects created, can substantially change (Meinel and Neubert, 2004; Neubert and Herold, 2008; Smith and Morton, 2008; Van Coillie et al., 2008). Differing from the automatic image segmentation algorithms, objects can be created using the cartographic limits contained in spatial geodatabases. This approach is known as *Parcel-Based Image Analysis* and has some advantages regarding to other image analysis techniques, the most important being the possibility to directly link the information of the image to the information contained in a database (Berberoglu and Curran, 2004; Walter, 2004). Moreover, for many land use mapping applications, parcel-based classification has been reported to be more accurate than pixel-based classification (Pedley and Curran, 1991; Janssen and Molenaar, 1995; Aplin et al., 1999; Berberoglu et al., 2000; Volante et al., 2007).

Once object definition is resolved, the next step is to accurately describe each group of pixels in order to facilitate the correct classification of the object. Different commercial software tools have been made available over the last several years, providing a variety of features to describe the properties of the objects and their mutual relations. These features can be grouped into spectral, textural, shape, thematic attributes, relative to other objects in the same or different segmentation levels and relative to the global image (Baatz et al., 2004). Our need for a tool to automate the descriptive feature extraction process, allowing us to design and incorporate new sets of features describing objects from different perspectives, evaluating and comparing their performance, led us to develop FETEX 2.0, an interactive computer program for image object-oriented feature extraction. The software was written in IDL 6.2 and it can be used on ENVI 4.2 or higher. Our aim with this program is to develop new object descriptive features, some of them not included in commercial software tools, designed to characterize specific types of parcels, and with the capacity to adapt certain computation parameters to particular problems. These features can eventually be used with any classifier in order to assign a class to each object. The software requires, as input data, images and vectorial files containing the polygon boundaries in ESRI shapefile (shp) format.

FETEX 2.0 does not include any segmentation algorithm, but it creates the objects according to the limits contained in the vectorial file. From each one of the objects created, spectral, textural, shape and structural features can be extracted. The structural features provide information about the distribution of elements inside each object, detecting and quantifying possible spatial patterns, very often relevant in identifying the land use/land cover of objects, especially when working in agricultural areas. For each object, the output is a feature vector ready to be used with the selected classifier. Information obtained with FETEX 2.0 can be used not only in the classification of the database objects, but also as ancillary information in agricultural inventories. Such ancillary information can be the number of trees in a parcel, their average size, planting distances, etc. Additional images and explanatory graphs about the features extracted that may be useful for interpretation of results can be obtained as well.

FETEX 2.0 is designed to work with land use/land cover databases in order to help in the process of classification of the existing parcels, or also to determine the changes that have occurred in a database comparing the current classified image with the old database. It has been applied successfully in the feature extraction phase in several updating land use/land cover cartography processes (Ruiz et al., 2009). Interested users are most likely to be among the cartographic research community and official cartographical institutions devoted to updating and maintaining large land use/land cover databases. A limited version of FETEX 2.0 is available at the Geo-Environmental Cartography and Remote Sensing Research Group (CGAT) website (http://cgat.webs.upv.es).

2.- EXTRACTION OF DESCRIPTIVE FEATURES WITH FETEX 2.0

The main reason for developing the program was to create a tool for supporting the process of classification and updating of land use/land cover spatial databases from an object-based perspective. The extraction of valuable features for this process is essential. FETEX 2.0 is designed to independently process each image-object to extract a variety of descriptive features useful to characterize the current land use/land cover. These features can be grouped into five categories: spectral, textural, structural, shape and those extracted from ancillary data. In this section, the features are briefly described or referenced.

2.1.- Spectral features

Spectral features provide information about the spectral response of objects, which depends on land coverage types, state of vegetation, soil composition, construction materials, etc. These features are especially useful in the characterization of spectrally homogeneous objects, such as herbaceous crops, fallow fields or compact industrial areas. This group of features constitutes the traditional information derived from any type of multispectral imagery. In addition to the original spectral bands, any combination, ratio, or transformation (principal components, tasselled cap bands, etc) can be included as complementary bands in the input raster file to be processed.

For each band contained in the input raster file, the values of mean, standard deviation, minimum, maximum, range, sum and majority of the pixel values inside each object can be calculated.

2.2.- Texture features

The texture informs about the spatial distribution of the intensity values in the image, providing information about contrast, uniformity, rugosity, regularity, etc. A considerable number of quantitative texture features and approaches have been reported using different methodologies. Traditionally, they are computed considering the neighbourhood of each pixel on the image. In our case, each texture feature value is referred to a particular object, since it is extracted from each group of pixels that constitute an object. The simplest manner to characterize texture is based on the first order histogram features. Features such as *kurtosis* and *skewness*, representing the distribution of values of the histogram of an object, are included in FETEX 2.0. The most widely used set of features is that proposed by Haralick et al. (1973), based on the grey level co-occurence matrix (GLCM) and also called second order histogram features. Up to seven of these features can be extracted by FETEX 2.0: *contrast*, *uniformity*, *entropy*, *variance*, *covariance* or *product moment*, *inverse difference moment*, and *correlation*. Since an object-oriented approach is used, only one GLCM is computed for each object, describing the co-occurrences of the pixel values that are separated at a distance of one pixel inside the polygon, and considering the average value of four principal orientations (0º, 45º, 90º and 135º) in order to avoid the influence of the orientation of the elements inside the objects, keeping in mind a potential classification process. Therefore, only one value for every GLCM feature is computed for each object. Although the *mean* of the GLCM is one of the most widely used features in texture image classification problems at the pixel level, due to its very high correlation to the mean value of the original band, this feature has been intentionally excluded from the set of GLCM features.

Another powerful feature is the *edgeness factor*, that represents the density of edges present in a neighbourhood. Sutton and Hall (1972) proposed the following formula to compute the *edgeness factor* g:

$$g(d) = \sum_{(i,j)\in N} \left\{ \left|I(i,j) - I(i+d,j)\right| + \left|I(i,j) - I(i-d,j)\right| + \left|I(i,j) - I(i,j+d)\right| + \left|I(i,j) - I(i,j-d)\right| \right\} \quad (1)$$

where g is computed as a function of the distance d between pixels of an image I in a neighbourhood N. Due to the good performance of this feature in different landscape classification problems (Ruiz et al., 2002; 2004), it has been included in the program, and the *mean* and the *standard deviation* of the *edgeness factor* for each parcel is computed.

2.3.- Wavelet-based texture features

Although the basic ideas of wavelets existed since the beginning of last century, the applied mathematical models were developed in the mid-eighties. A review and mathematical description of wavelets can be found in Bultheel (1995), and Walker (1999). The use of the wavelet transform for texture analysis was first proposed by Mallat (1989). Since the texture of an image is a function of the scale, an advantage of wavelet decomposition is that it provides a unified framework for multiscale analysis. The wavelet transform allows for the decomposition of a signal using a series of elemental functions called *wavelets* and *scaling*, which are created by the scaling and translation of a base function, known as the *mother wavelet*:

$$\psi_{s,u} = \frac{1}{\sqrt{s}}\psi\left(\frac{x-u}{s}\right),\ s \in \Re^{+},\ u \in \Re \tag{2}$$

where s governs the scaling and u the translation. The wavelet decomposition of a function is obtained by applying each of the elemental functions or wavelets to the original function:

$$Wf(s,u) = \int_{\Re} f(x)\frac{1}{\sqrt{s}}\psi^{*}\left(\frac{x-u}{s}\right)dx \tag{3}$$

In the practice of image analysis, the extension to a 2-D discrete function is usually performed by means of a product of 1-D low-pass and high-pass filters. As a result, the wavelet transform decomposes the original image into a series of images with different scales, called trends and fluctuations. The former are averaged versions of the original image, and the latter contain the high frequencies at different scales or levels. Since the most relevant texture information is lost in the lowpass filtering process, only fluctuations are used to calculate texture descriptors. If the inverse transform is applied to the fluctuations, three reconstructed images, or *details*, are obtained: horizontal, vertical and diagonal. This process is called multiresolution analysis.

Different texture features have been extracted from wavelet details or fluctuations, such as the local energy (Randen and Husoy, 1999), variance filter (Ferro and Warner, 2002), histogram signatures (Simard et al., 1999), or co-occurrence features (Van de Wouwer et al., 1999; Ruiz et al., 2004).

The application FETEX 2.0 includes some texture features based on the wavelet transform. Seven families of wavelet functions (Haar, Daubechies, Coiflet, Meyer, Symlet, Shannon and Battle-Lemarié) can be applied over the image objects. Defining the support of a wavelet function as the smallest closed interval, outside of which the function is zero (Bultheel, 1995), different supports have been defined for each wavelet family, following the work of Fernández-Sarría (2007). A total of eight Haralick's features derived from the GLCM can be extracted from the image containing the sum of the reconstructed details (*mean*, *contrast*, *uniformity*, *entropy*, *variance*, *covariance*, *inverse difference moment*, and *correlation*), as well as the *mean* and *standard deviation* of the *edgeness factor*.

However, applying the wavelet transform using an object-oriented approach may be a problem when large supports are used, since a higher proportion of neighbour pixels located outside the analyzed object will be considered in the transformation process. Two measures are followed to reduce this effect: First, an erosion filter using a circular structuring element with a diameter size equal to the support of the wavelet function is applied to the final image. A limitation of this is that small and/or narrow objects will be completely eroded, and subsequently omitted from the characterization of the features that belong to this group. Secondly, even if up to three levels of decomposition are included for computation in FETEX, only the first level is enabled in the current version, in order to avoid the decimation of the image to the point that the object practically dissapears when the direct transform is applied. This effect will be negligible when working with large objects.

2.4.- Structural features

Structural features provide information of the spatial arrangement of different elements in the object, in terms of randomness or regularity of the distribution of the elements. This is the case of alignments or regular patterns that are present in different man-made lanscapes, such as the planting patterns of crops and trees in agricultural plots (Recio et al., 2006; Ruiz et al., 2007). The identification of regular planting patterns can be particularly useful in agricultural classification, as reported by several authors (Trías-Sanz, 2006; Helmholz et al., 2007; Ruiz et al., 2009; Recio, 2009; Hermosilla et al., 2010). Structural features computed in FETEX 2.0 are divided into two groups: the semivariogram and the Hough transform derived features.

2.4.1.- Features extracted from the experimental 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. This is a particularly suitable tool in the characterization of regular patterns. The expression which describes the experimental semivariogram of a continuous variable is:

$$\gamma(h) = \frac{1}{2N} \sum_{i=1}^{N} \left[z(x_i) - z(x_i + h) \right]^2 \qquad (4)$$

where $z(x_i)$ represents the value of the variable in position x_i, N is the number of pairs of data considered and h provides the separation between elements in a given direction.

The semivariogram has been widely employed in digital image processing. Its usefulness in remote sensing has been demonstrated, complementing the spectral variables with information related to the spatial structure of the image (Carr, 1996; Durrieu et al., 2005). The relationship between the range of the semivariogram and the size of the pattern described by the objects of an image has been studied by Woodcock et al. (1988a, 1988b). Carr and Miranda (1998) used the slope in the origin as a feature directly related to the variability of the intensity values in these objects. Other works are focused on the extraction of descriptive features from the semivariogram of remotely sensed images. Thus, Chica-Olmo and Abarca-Hernandez (2000) computed the first value of that function in the neighbourhood of a pixel to characterize the texture of that neighbourhood. Maillard (2003) used all the semivariogram values, conferring more importance to the initial values, and less to the subsequent values. These and other authors (Jakomulska and Clarke, 2000; Ashoori et al., 2008; etc.) used different features extracted from the semivariogram computed in a window around a pixel in order to perform a classification.

The omnidirectional semivariogram can be obtained by averaging the semivariograms of all possible directions. However, this approach requires a long processing time. This semivariogram is obtained in FETEX 2.0 by computing, for each object, the mean of the semivariograms calculated in six different directions, ranging from 0º to 150º with a step of 30º. Afterwards, each semivariogram curve is smoothed using a Gaussian filter with a stencil of 3 positions, in order to reduce experimental fluctuations.

In homogeneous objects, semivariance values tend to be higher as the lag increases. However, when the elements inside an object are spatially arranged following a regular pattern, the semivariogram has a cyclic behaviour, and it is known as *hole-effect semivariogram* (Pyrcz and Deutsch, 2003). This type of behaviour is common in areas with a high level of human intervention, such as certain crops, urban or industrial landscapes. Figure 1 shows the experimental semivariogram curves of four parcels with different land uses. Figure 1a and Figure 1c present parcels containing tree crops that follow regular plantation patterns, their semivariograms being examples of *hole-effect semivariograms*. On the other hand, Figure 1b and Figure 1d do not present regular patterns or spatial cyclicity, and their semivariogram curves follow a monotonous rising trend.

The features extracted by FETEX 2.0 are based on the zonal analysis defined by a set of singular points on the semivariogram, such as the first maximum, the first minimum, the second maximum, etc., and are fully described in Balaguer et al. (2010). The semivariogram derived features are: *ratio variance at first lag*, *ratio between semivariance values at second and first* *lag*, *first derivative near the origin*, *lag value corresponding to the first maximum*, *mean of the semivariogram values up to the first maximum*, *variance of the semivariogram values up to the first maximum*, *area between the semivariogram value in the first lag and the semivariogram function until the first maximum*, *ratio between the semivariance at first local maximum and the mean semivariogram values up to this maximum*, *distance between the location of the first local maximum and the second local maximum*, and *distance between the first maximum and the first minimum*.

In terms of efficiency in processing time, instead of computing the semivariogram considering all the pixels inside each object, only a random selection of pixels is used, in order to reduce the processing time. A test was carried out in order to assess the influence of the percentage of pixels used in two processes: in the calculation of the semivariogram curve, and in the performance of the classification of a sample of N objects. The results show that semivariograms calculated using a reduced number of random pixels are very similar to those computed using all the pixels inside each object, as shown in the two examples of Figure 2.

Regarding the classification performance, Figure 3 shows a graph representing the overall accuracies obtained in a per-object classification using the set of features derived from the semivariogram described above. Ten classification processes have been compared. In each, a different percentage of pixels has been randomly selected for semivariogram calculation. The overall accuracy obtained using 100% of the pixels is 81.3%. The results reveal that the semivariogram derived features computed when using only 15% of the pixels describe the objects with an efficiency similar to that of when all the pixels are used, since they do not produce a significant reduction in the classification accuracy. Besides, the processing time is linearly reduced: 85% using only 15% of pixels, 75% considering a 25% and so on.

2.4.2.- Features derived from the Hough transform

The planting pattern and planting distances are key factors employed by photointerpreters to distinguish different crop typologies. Thus, once the information about global regularity of the parcel is extracted from the semivariogram analysis, the plantation pattern can be more profoundly analysed in order to obtain more specific descriptors that complement the semivariogram derived features. For this purpose, a variety of features based on the Hough transform are included in FETEX 2.0.

The first step in the extraction of these features is the location of trees, which is done using the local maximum filtering (LMF) method (Gourgeon, 1999) from high spatial resolution imagery. The LMF is based on the assumption that reflectance is highest at the tree apex and decreases towards the crown edge (Wulder et al., 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. However, this displacement has no negative effects because it equally affects all the maxima.

LMF method is applied over NDVI images using a circular kernel with variable size to detect adult trees. This size is automatically determined for each object by the position of the first maximum on the semivariogram curve, being constrained by the interval defined between two thresholds that are set by the user. If the first maximum is lower than the lower threshold, this threshold will be used as the diameter of the kernel. In a similar way, if the first maximum is greater than the upper threshold, the diameter of the kernel will be the upper threshold. Assuming a regular distribution of trees in a parcel, the kernel diameter is related to the average size of the trees contained in a parcel.

Most of these features are designed for the classification of agricultural tree orchards. In order to facilitate this task, two main groups of trees can be considered: adult trees, having a considerable canopy, and young trees, with almost no vegetation cover. A threshold defined over the NDVI image is selected in order to distinguish those two groups of parcels. In those parcels with a NDVI mean value lower than the defined threshold, instead of applying LMF over the NDVI image, trees are searched by using a local minimum filtering (LmF) over the infrared (IR) band. This variation is used in order to locate the young trees recently planted. The result is a binary image where each located tree is represented by a pixel. In both cases, adult and young trees, pixel location must accomplish an additional condition: the maximum in NDVI band must be greater than a threshold fixed by the user and the minimum in IR band must be lower than a threshold, which must be empirically defined depending on the image characteristics. From this binary image, main tree alignments are extracted and characterized applying the Hough transform (Hough, 1962).

The **Hough transform** is a method that can be used in image processing to locate curves that can be parameterized as straight lines, polynomials or circles. This method has been widely used on images for row detection in agricultural crops (Reid and Searcy, 1986; Leemans and Destain, 2006; Gée et al., 2008). Structural information derived from the Hough transform has also been used for automatic classification and characterization of agricultural landscapes. Chanussot et al. (2005) applied the Fourier transform over a vineyard image, and then, the Hough transform for estimating and representing the crop orientation. Trías-Sanz (2006) employed structural properties based on orientation features to discriminate between different vegetation covers. He applied the variogram transformation and then, over the resultant image, the Hough transform, obtaining the orientation histogram. Helmholz et al. (2007) used the orientation information directly derived from the Hough transform to separate between tilled and untilled plots based on the existence of a minimum number of parallel lines.

The principle of the Hough transform is based on the fact that an infinite number of straight lines can go through a single point of the plane. The purpose of the method is to determine which of these theoretical lines go through more points in the image, that is, to find the best fitting lines to the set of points that are present in the image. The method is based on the transformation of the coordinates from a Cartesian image space to a polar coordinate space. A point in the Cartesian space corresponds to a sinusoid in the polar space, representing the parameters of the lines passing through that point. A line in the Cartesian space is defined by the intersection of two or more sinusoids in the polar space.

After thresholding the polar space to remove lines passing through a small number of points, remaining lines are grouped into a histogram of frequencies for all directions ranging from 0º to 180º. When some regularity in their spatial arrangement exists, two histogram maxima appear, corresponding to the principal directions or alignments of trees in the parcel. Figure 4 shows an example of this: a tree parcel (Figure 4a); the binary image with the local maxima representing the location of trees, with the orientations of the two principal alignments superimposed (Figure 4b); the result of the Hough transform (Figure 4c). The existence of points where several curves converge indicates the presence of alignments in the Cartesian domain. Grouping these values in a histogram of frequencies, the two orientations of the principal alignments in the parcel are easily differentiated at 75º and 161º (Figure 4d). By isolating these orientations, the angular difference between them provides information about the orthogonality of the alignments. The distance between the points where the curves converge on the same direction in the Hough domain correspond to the distance between the lines following that direction. These distances are used to describe the planting pattern size of tree crops along the two main orientations (Figure 5).

A set of additional features related to the regularity in the distribution of trees are extracted from this transformation and the histogram of orientations. These features are: *proportion of points included in the principal and secondary direction with respect to the total amount of points*; *mean, median* and *standard deviation of the distances between straight lines in the principal and secondary directions; proportion of straight lines in the principal and secondary directions;* and *angular difference between the two principal directions*.

2.5.- Shape features

The shape features computed in FETEX 2.0 inform about the shape complexity of the objects, and are mainly based on ratios between the area and the perimeter of the objects. These descriptors, extracted directly from the geometric definition of the polygons contained in the database (parcels) can help to distinguish and identify different elements with particular shapes, such as roads, rivers, circular plots, etc.

The features available in the application are: *compactness* (Bogaert et al., 2000), *shape index* and *fractal dimension* (Krummel et al., 1987; McGarigal and Marks, 1995) (see Table 1). The area and perimeter of each object are also computed.

2.6.- Ancillary data

Depending on the algorithm used in a subsequent classification process, discrete variables can be included as descriptive features. Some studies (Rogan et al., 2003; Recio et al., *in press*) have shown that the combination of the historical land use of the parcels contained in an old database with spectral features may increase the overall accuracy of the classification. Some other discrete information, such as soil type and composition (Huang and Jensen, 1997), irrigation type, etc. can sometimes be useful to better describe the parcels or polygons. If this information is included in the spatial geodatabase as an input in FETEX 2.0, it can also be added as an output to the descriptive feature vector of each parcel.

Any other georreferenced information in raster format can also be added as extra input to extract information and characterize the objects. Thus, digital terrain models (elevation, slope or aspect) (Hoffer, 1975; Hutchinson, 1982), distance maps (Debeir et al., 2002; Mas, 2003; Recio et al., 2010), results of a *per-pixel* classification (Recio, 2009) or others, can be added as additional bands in order to compute statistics to describe the parcels.

3.- THE PROGRAM

3.1.- Graphic User Interface

The Graphic user interface of FETEX 2.0 is a window menu divided in five frames (Figure 6): 1.- Input files, 2.- Output files, 3.- Feature selection, and 4.- Feature parameters definition.

3.1.1.- Input files

Image formats supported by FETEX 2.0 must be georeferenced and are those supported by ENVI (GeoTIFF, JPG2000, ENVI binary, ERDAS img, etc.). Limits of cartographic objects (parcels) must be contained in a ESRI shapefile spatial data format (.shp). In order to correctly superimpose both data, the image and the shapefile, they should be in the same spatial reference system.

FETEX 2.0 is able to work with large datasets of several images and shapefiles. In the case that a parcel (object) is represented along several image files, the program will internally build a mosaic and extract the final descriptive features from this new composed image.

3.1.2.- Output files

As a result of processing the image for object information extraction, an output table containing the values of the descriptive features selected (columns) for every object processed (rows) is obtained. This table can be available in four different formats: dBase, shapefile, ASCII and the format required by See5 software, which contains the C5.0 algorithm to generate decision trees.

In addition to the table with all the feature values needed for the classification of the objects, FETEX 2.0 provides the option of generating a set of screenshots and graphs that may be helpful for the interpretation of the results (Figure 7). The set of screenshots obtained for every object includes a color or grey level image of the object, the image of the wavelet details, image files of the GLCM of the original image and the wavelet details, the semivariogram graph, a binary image of the tree locations automatically detected, its Hough transform graph, and the binary image of the tree alignments. Additionally, a dbf file containing the semivariogram for each analyzed object can be generated.

3.1.3.- Feature selection

In this frame, the user can select the groups of features to be extracted from the objects. There are seven main groups of features: spectral, texture features based on the GLCM, wavelet derived texture features, descriptive parameters derived from the semivariogram, Hough transform based features, shape features, and qualitative features from a database.

On the right side of the frame, there are three drop-down lists for the selection of the image bands from which the GLCM, wavelet and semivariogram features will be computed.

The last item in this menu enables us to use descriptive information from the input shapefile database as an additional descriptive feature. If the *Database feature* option button is enabled, the field of the shapefile database containing the descriptive feature must be selected from the adjoining drop-down list.

3.1.4.- Feature parameters definition

This frame is divided in three sections. In the first section, three general parameters of the process can be fixed: *Minimum parcel size* controls the minimum area of a polygon to be processed, avoiding very small polygons that may difficult a correct characterization. *Parcel perimeter buffer* is used to reject the peripheral pixels of the polygon in the analysis, in order to avoid the inclusion of pixels that are external to the object due to geo-referencing errors or misregistration between the database and the image. The values of the droplist represent the thickness of the rejecting buffer in pixels. *NDVI bands* droplist allows for the selection of the two image bands required for computing the NDVI: the IR and red bands.

The second section of this frame (*Analysis options*) allows for the selection of the specific features that can be obtained from the different feature groups, as well as the methodological parameters involved.

In the first tab, seven statistical features can be selected to be computed from each object. These features are computed for every band of the input image.

The second tab corresponds to the texture features. The number of grey levels to be considered in the computation of the GLCM can be chosen. The selection of this parameter is important, because the use of many grey levels does not necessarily mean an increase in the efficiency of the descriptors, but greatly increases the time consumed for computation. Furthermore, in objects containing a low number of pixels, many grey levels in the computation of the GLCM can make the characterisation of the distribution of the values in the matrix difficult.

The wavelet tab controls the wavelet function family and the support used to perform the wavelet transform. Higher support values will require longer processing time. The number of grey levels to be considered in the computation of the GLCM can also be chosen.

Two parameters can be controlled in the semivariogram tab: the *maximum Semivariogram lag size*, and the *Percentage of pixels* from an object that are used to estimate its semivariogram, as analyzed at the end of section 2.4.1.

In the Hough transform tab, several thresholds related to the automatic process to detect the trees inside a parcel can be established. The *Initial NDVI (parcel)* parameter allows for the definition of a threshold for the mean NDVI of the object. For those objects with a mean NDVI higher than this value, the LMF method is applied using the NDVI image to locate the trees. On the other hand, for the objects with a mean NDVI lower than this threshold value, the trees are located applying the LmF method using the IR band. Afterwards, two conditional thresholds must be established: those pixels located with the LMF method must have a NDVI value higher than the *NDVI threshold* to be accepted as a tree, whereas the IR band values of the pixels located with the LmF method must be lower than the *IR band threshold*.

Additionally, a selection of the threshold values used to define the size of the searching window must be done, specifically the minimum and maximum *Window diameter* values. These values must be in concordance with the minimum and maximum sizes of the trees, in pixels, that are present in the specific geographic area.

The last tab corresponds to the selection of the shape features to be computed.

The last part of this frame (*Attributes in the shapefile*) first allows for the selection of the object identifier field in the shapefile of the database (*ID*), which must be an integer number. In addition to this, when a field containing the class of the training samples exists in the database, this can be selected in the last drop-down list (*Samples*). This information will be added at the end of the row of the feature vector corresponding to each object. The parcels that are not training samples will have a question mark at the end of the row. This field is required in order to obtain a *See5* file format output.

3.2 Future improvements

FETEX 2.0 has been designed to work with large datasets, including images and shapefiles. In addition, some effort has been put to reduce the time needed to compute the different procedures used in the program, this is particularly important when a high number of objects must be processed.

The program allows for the extraction of a wide range of features from images and databases, some of them mainly focused on agricultural landscapes, with the final goal of describing the objects in depth in order to improve their classification. However, the program is intended to be a dynamic tool that progressively incorporates new feature extraction algorithms, as well as different types of spatial data which are currently more widely available,. The design and analysis of new descriptive features coming from different sources of information (airborne lidar systems, satellite radar images, etc.) will continue in order to advance in the description of objects. Useful three-dimensional information about the objects and the elements they may contain can be extracted from lidar data, complementing the current information available. In a different way, high resolution radar imagery can provide extra information about the roughness of the surfaces, which may complement the previous features. All these new sources of information are becoming more widely available to the user, and new tools to integrate and process the data will be needed.

4.- APPLICATION EXAMPLE: OBJECT-ORIENTED CLASSIFICATION OF AN AGRICULTURAL DATABASE

An object-oriented classification application example has been carried out using the descriptive features extracted with FETEX 2.0. The test has been performed using data from a rural area in the province of Castellón, on the Mediterranean coast of Spain. A series of aerial images acquired in August 2005 with a Digital Mapping Camera (DMC) have been used, with a spatial resolution of 0.5 m/pixel and three spectral bands (green: 0.50-0.65 μm; red: 0.59-0.675 μm; and near infrared: 0.675-0.85 μm). A total of 616 training samples and 2438 evaluation samples have been selected from the cadastral polygons. The reference data used for evaluation have been obtained combining field work and photointerpretation. According to the type of landscape, ten different classes have been defined in the classification: *Arable fields, Buildings, Carob-trees, Citrus orchards, Irrigated fields, Olive trees, Roads, Shrub-lands,* and *Young citrus orchards*. Figure 8 shows some image-object examples of each class.

A set of different descriptive features has been computed using FETEX 2.0. They can be grouped as follows: (1) Spectral features: Mean, standard deviation, minimum and maximum from each band, and NDVI; (2) Texture features: GLCM derived features, *edgeness factor*, 1st order descriptors, and wavelet based features computed from the red band; (3) Structural features: Hough transform and semivariogram derived features computed from the infrared band; and (4) Shape features.

Two classification methods have been used: Linear discriminant analysis (LDA), and decision trees computed using the C5.0 algorithm and combined with the boosting multi-classifier method. The classifications obtained have been evaluated by means of the error matrix (Congalton, 1991), from which the overall accuracy rate, the user's and producer's accuracies for every class have been computed.

Four tests per classification method have been done to independently evaluate the performance of each descriptive feature group. An additional classification has been performed combining all features. Table 2 shows the overall classification accuracies obtained using the different groups and combinations of descriptive features. In both classification methods, the use of all the features from the different groups together sharply increases the overall accuracy rate of the classification. Additionally, no significant differences in overall accuracy are found between both methods when all the feature groups are used, showing that the influence of the classifier is not crucial when an exhaustive and complementary set of descriptive features is used. However, the use of independent sets of features may introduce some differences in the overall accuracy depending on the classification method used. Thus, using only spectral features, LDA provides a better accuracy (65.5%) than decision trees (60%), but the latter increases the accuracy (62.1%) with respect to the LDA method (57.8%) when only structural features are included for classification. These differences may be due to the fact that the distribution of values of the two groups of features, spectral and structural, are subject to specific ranges, and both classification methods manage this information in different manner.

In order to study the influence or discriminant power that the variables (descriptive features) have on the classification, two approaches have been employed: forward stepwise LDA and the comparison of the percentage of use of each specific variable in all the decision trees created using the method of boosting. Figure 9 shows the per-class average of user's and producer's accuracies, and the overall classification accuracy when the 24 first features are progressively included in the discriminant model. Figure 10 shows the percentage of use for the 24 descriptive features most used by the classifier over the training objects.

The shape feature *fractal dimension* is the most frequently used in the decision trees and the first discriminant feature selected in the stepwise LDA, allowing for the discrimination of class *Roads* very efficiently, due to the characteristic long shape of the polygons that represent this class. Particularly interesting is the fact that, always, some variables coming from the four different groups considered are selected among the most relevant features. Using this short group of variables the overall accuracy becomes stable, independently of the inclusion of additional variables in the classification set (Figure 9). This illustrates again their complementarity, as well as the possibility to increase the efficiency of the classification not only in terms of accuracy, but also in terms of reduction of the number of variables to be used, by using only a selected group of features with low correlation.

5.- SUMMARY

A software program, FETEX 2.0, that extracts a set of descriptive features from image-objects and geodatabases is presented. A description of the features, classified into seven different groups and providing different and complementary information about the object, is carried out. Some of them are particularly useful to characterize and classify agricultural landscapes and have been presented for the first time here.

This software application generates an output table containing the object feature vectors available in different formats, ready to use with different classifiers included in statistical packages. Additionally, different types of descriptive graphs and images can be obtained to facilitate the interpretation of processes and results. A classification example has been performed, showing the wide range of information obtained from each object. In this application example, it has been shown how the use of different types of variables provides a complete description of the object, increasing the accuracy of the land use/land cover classification. The software program presented here allows for the computation of all these variables for their application to object-oriented classification, particularly interesting for agricultural mapping.

FETEX 2.0 can be considered to be a dynamic program in a continuous updating process in order to incorporate new sources of data, new methods and features, and with the ability to be oriented to specific applications. A limited version of FETEX 2.0 is available at the Geo-Environmental Cartography and Remote Sensing Research Group (CGAT) website (http://cgat.webs.upv.es).

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Annexe: Description and codification of the features extracted by FETEX 2.0

Spectral Features (number indicates the band)			**Hough transform features**	
MEAN1	Mean value of band 1		ANG_DIF	Angular difference between the two principal directions
STDEV1	Standard deviation value of band 1		ANG1PERC	Proportion of straight lines in the principal direction
MIN1	Minimum value of band 1		ANG2PERC	Proportion of straight lines in the secondary direction
MAX1	Maximum value of band 1		RHO1MEAN	Mean of the distances between straight lines in the principal direction
RANGE1	Range of values of band 1		RHO1 STDEV	Standard deviation of the distances between straight lines in the principal direction.
SUM1	Summatory of values of band 1		PT1PERC	Proportion of points included in the principal direction
MAJORITY1	Mode of values of band 1		PT1NORM	Proportion of points included in the principal direction normalized by area
MEANNDVI	Mean value of NDVI		RHO1MEDIAN	Median of the distances between straight lines in the principal direction
STDEVNDVI	Standard deviation value of NDVI		RHO2MEAN	Mean of the distances between straight lines in the secondary direction
MINNDVI	Minimum value of NDVI		RHO2 STDEV	Standard deviation of the distances between straight lines in the secondary direction.
MAXNDVI	Maximum value of NDVI		PT2PERC	Proportion of points included in the secondary direction
RANGENDVI	Range of values of NDVI		PT2NORM	Proportion of points included in the secondary direction normalized by area
SUMNDVI	Summatory of values of NDVI		RHO2MEDIAN	Median of the distances between straight lines in the secondary direction
Texture Features			**Semivariogram based features**	
MEAN_EDG	Mean value of edgeness factor		RVF	Ratio between the values of the total variance and the semivariance at first lag
STDEV_EDG	Standard deviation of edgeness factor		RSF	Ratio between semivariance values at second and first lag
UNIFOR	GLCM Uniformity		FDO	First derivative near the origin
ENTROP	GLCM Entropy		FML	First maximum lag value
CONTRAS	GLCM Contrast		MFM	Mean of the semivariogram values up to the first maximum
IDM	GLCM Inverse Difference Moment		VFM	Variance of the semivariogram values up to the first maximum
COVAR	GLCM Covariance		RMM	Ratio between the semivariance at first local maximum and the mean semivariogram values up to this maximum
VARIAN	GLCM Variance		DMM	Distance between the first maximum and the first minimum
CORRELAT	GLCM Correlation		**Shape features**	
SKEWNESS	Skewness value of the histogram		COMPACT	Compactness
KURTOSIS	Kurtosis value of the histogram		SH_INDEX	Shape Index
Wavelet based features			FRACTAL	Fractal dimension
MEAN_W1	GLCM Mean of the details image		AREA	Area
UNIFOR_W1	GLCM Uniformity of the details image		PERIMETER	Perimeter
ENTROP_W1	GLCM Entropy of the details image		**Ancillary data features**	
CONTRAS_W1	GLCM Contrast of the details image		ANCILLARY	Ancillary data from database
IDM_W1	GLCM Inverse Difference Moment of the details image		**Processing information**	
COVAR_W1	GLCM Covariance of the details image		PROCESSED	Processing information
VARIAN_W1	GLCM Variance of the details image		**Training sample identification**	
CORRELAT_W1	GLCM Correlation of the details image		SAMPLE	Training sample class
MEAN_EDG_W1	Mean value of edgeness factor of the details image			
STDEV_EDG_W1	Standard deviation of edgeness factor of the details image			

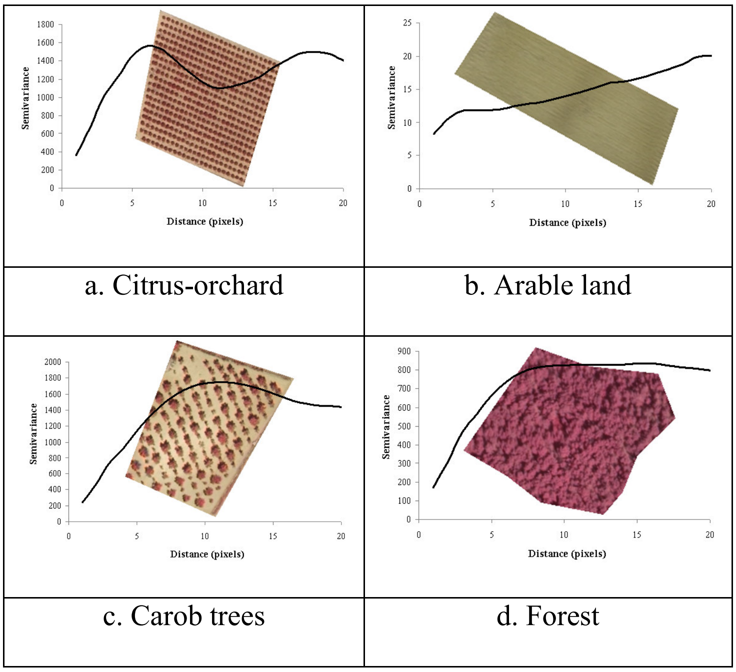

Figure 1. Parcels with different land use and their respective experimental semivariogram superimposed. Distance in pixels is in abscissas, and semivariance values are represented in ordinates.

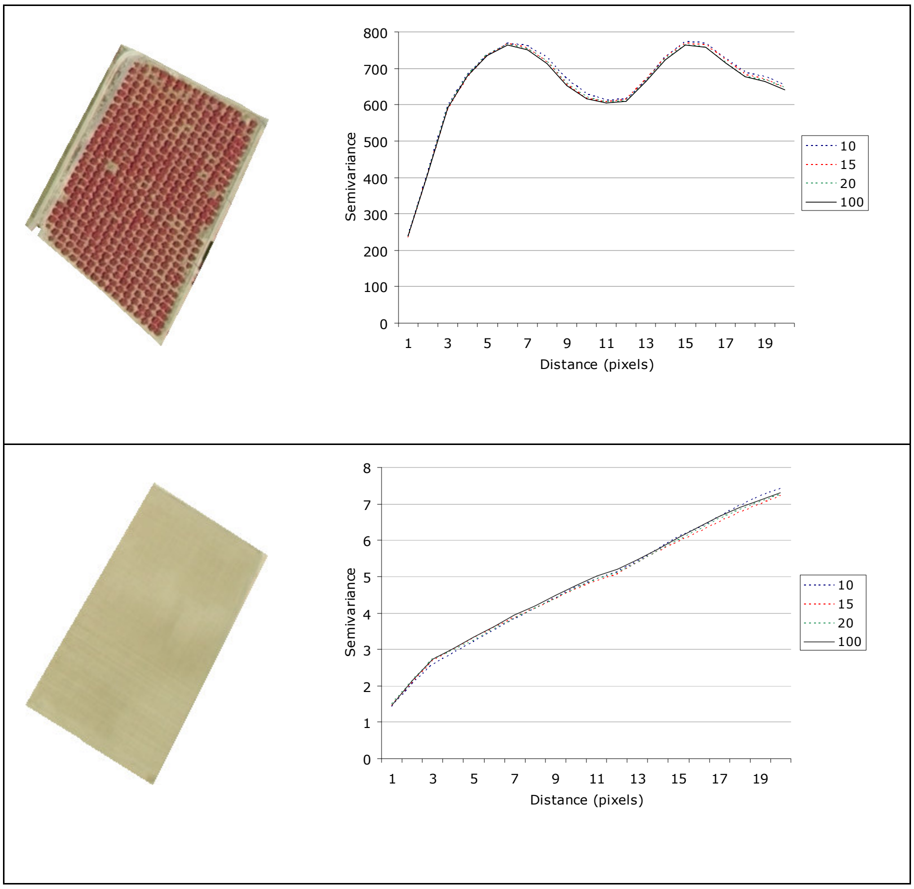

Figure 2. Semivariograms computed using different pixel percentages (10, 15 and 20) compared to semivariograms computed using all pixels in object.

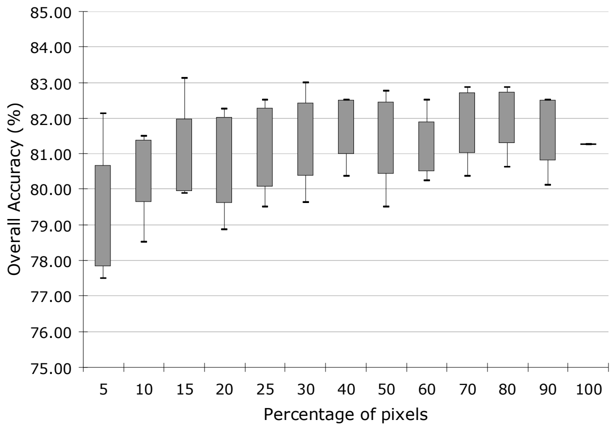

Figure 3. Box and whiskers graph representing overall accuracies of a series of 10 classifications for each pixel percentage used to compute semivariogram. Whiskers represent maximum and minimum values; boxes represent one standard deviation apart from mean values.

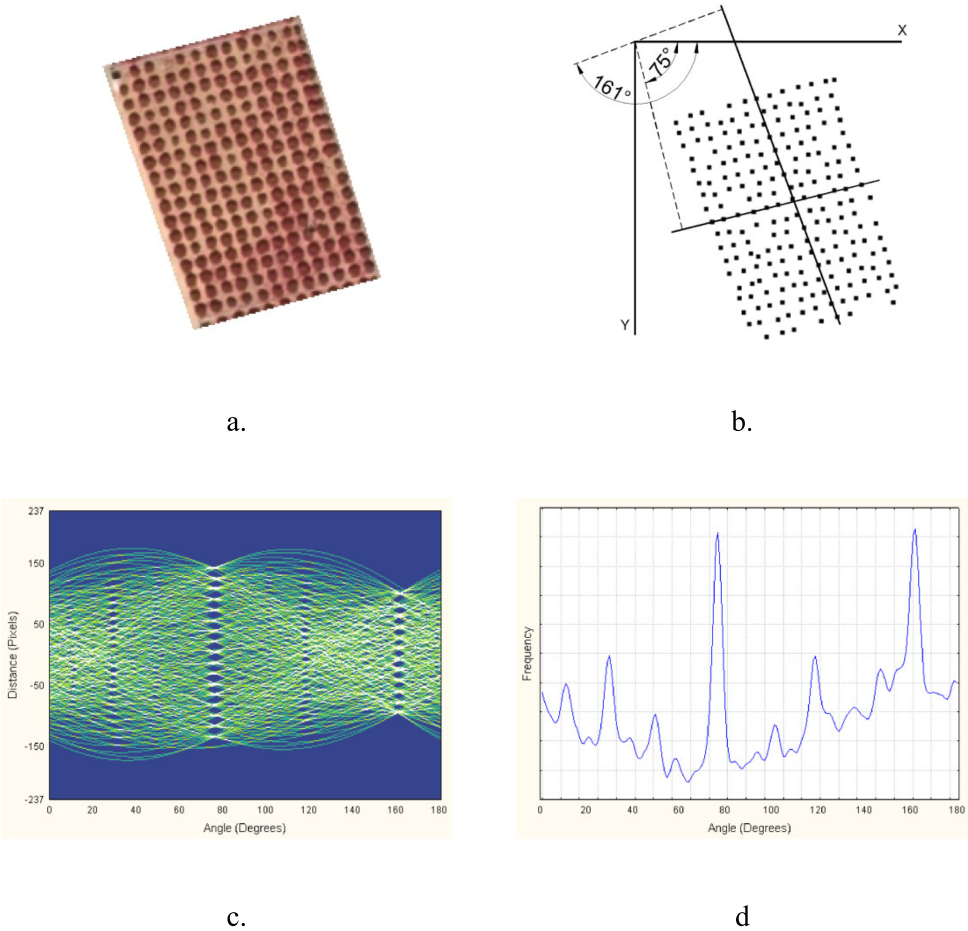

Figure 4. Example of application of the Hough transform method: (a) object in image space; (b) local maxima detection; (c) Hough transform space; (d) histogram of coincidences in different directions. Main directions are extracted at 75º and 161º.

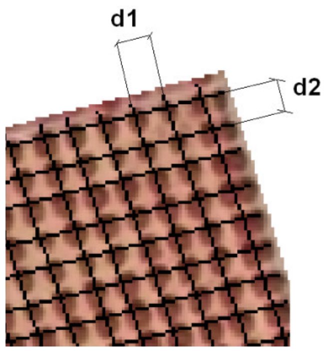

Figure 5. Extraction of planting pattern distances.

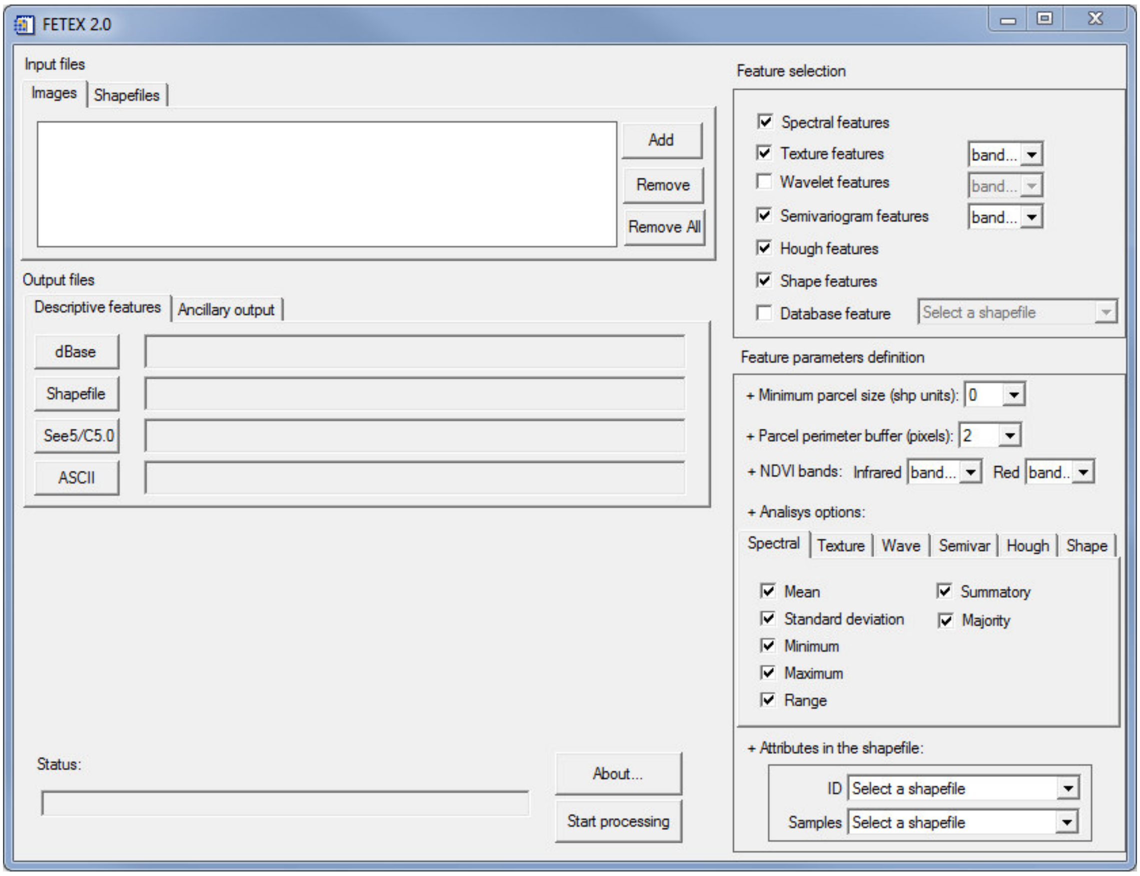

Figure 6. Graphic user interface of FETEX 2.0.

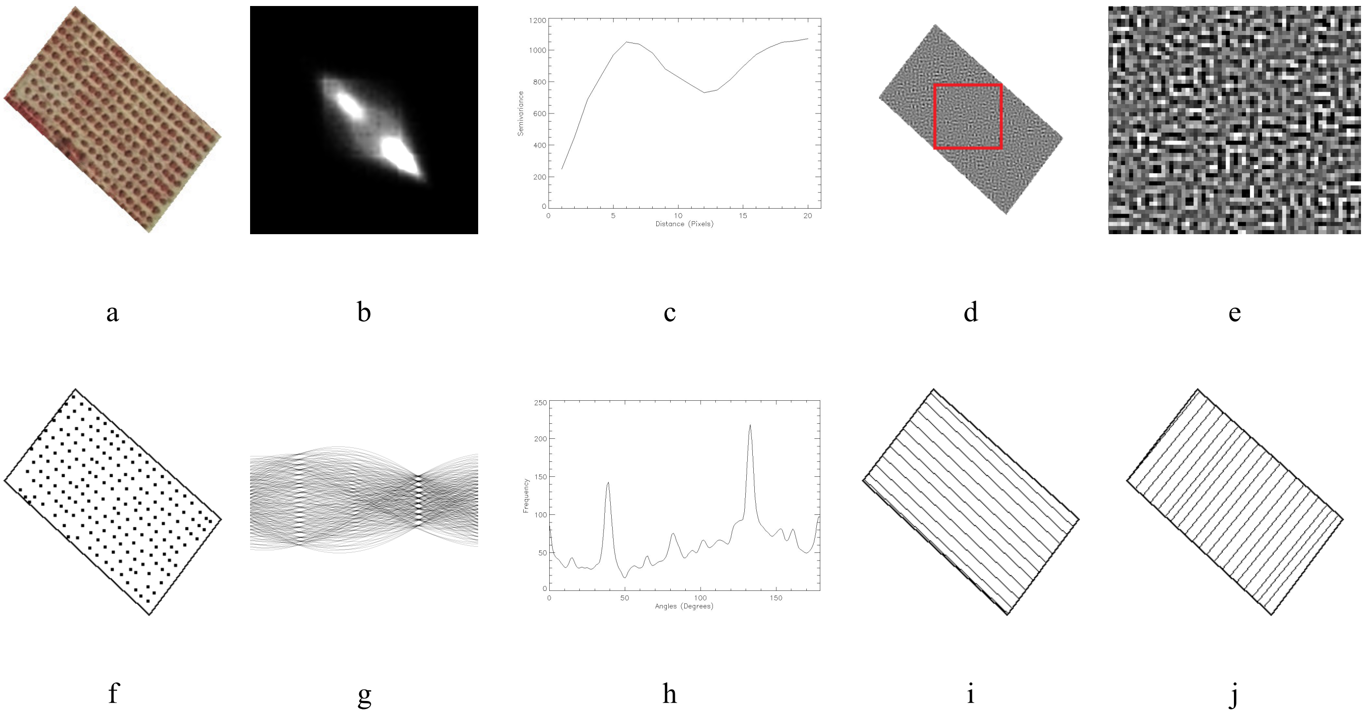

Figure 7. Examples of screenshots generated by FETEX 2.0 in a citrus crop parcel: (a) Color infrared image of object; (b) grey level image representation of the GLCM; (c) semivariogram graph (with *hole-effect* presence); (d) sum of details of wavelet decomposition (Coiflet, size 24 pixels); (e) detail of (d); (f) local maxima detected representing trees; (g) Hough space representation of local maxima; (h) Hough transform directions histogram; (i) alignments in main direction; (j) alignments in second direction.

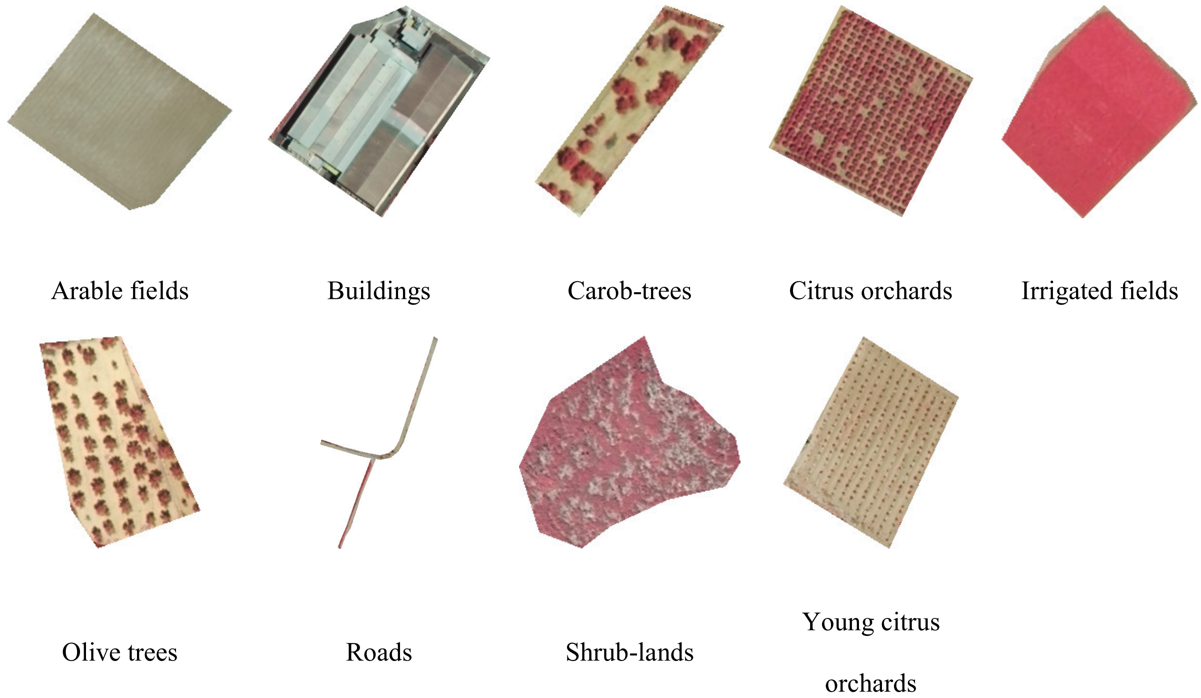

Figure 8.- Image-object examples, in color infrared composition, of classes considered for classification.

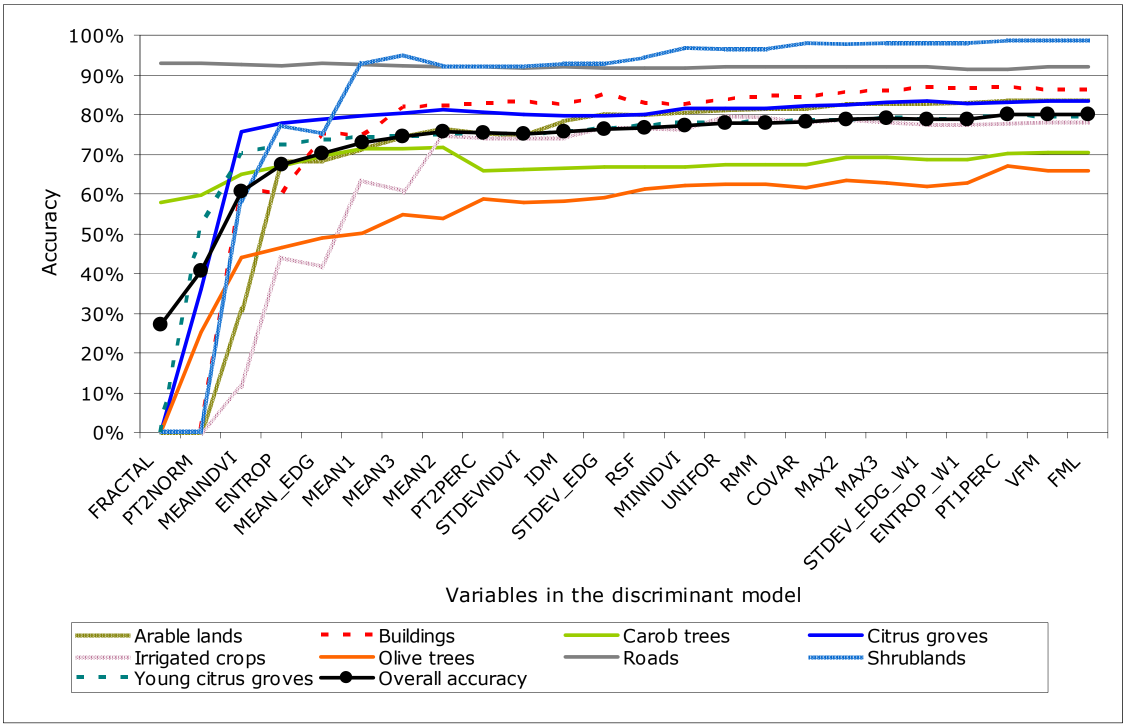

Figure 9.- Overall classification accuracy and *per-class* accuracies when new variables are progressively included into the discriminant model.

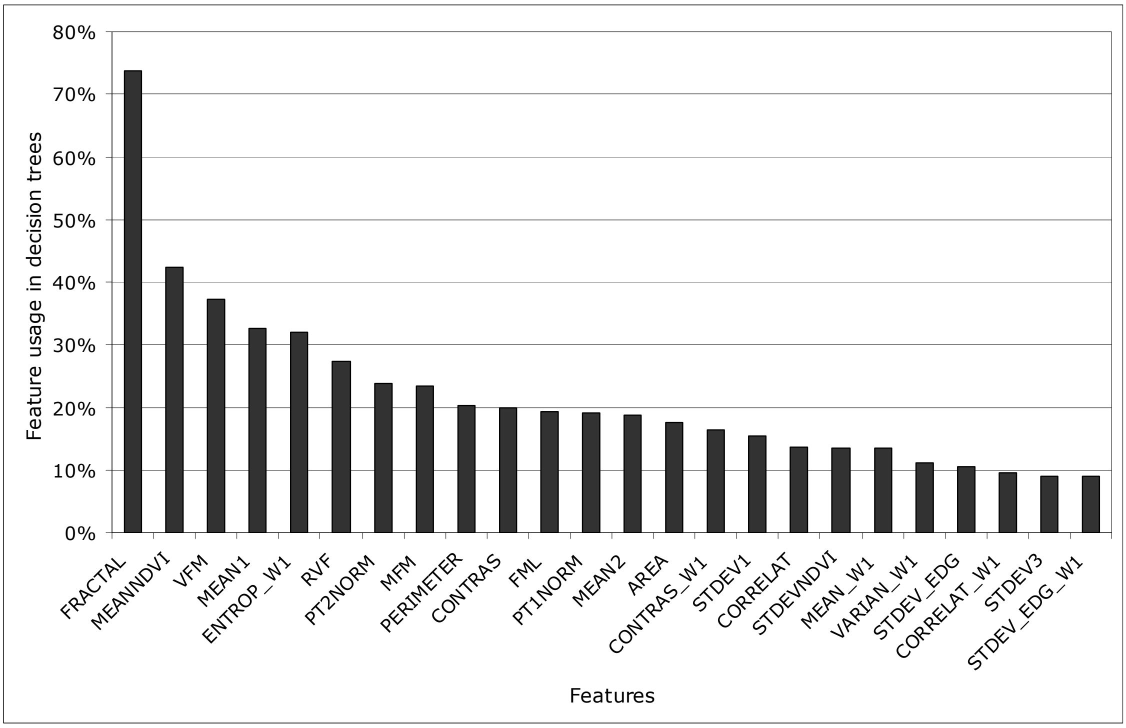

Figure 10.- Feature percentage of use in decision tree construction.

Table 1.-Shape parameters computed in FETEX 2.0.

$C = \frac{4 \cdot \pi \cdot Area}{Perimeter^2}$	$SI = \frac{Perimeter}{4 \cdot \sqrt{Area}}$	$FD = 2 \cdot \frac{\log\left(\frac{Perimeter}{4}\right)}{\log(Area)}$
a. Compactness	b. Shape index	c. Fractal dimension

Table 2. Overall classification accuracies using different groups and combinations of descriptive features

	Classification method	
Descriptive feature groups	**Linear discriminant analysis**	**Decision trees (C5.0)**
Spectral features	65.5%	60.0%
Texture features	65.4%	66.7%
Structural features	57.8%	62.1%
Shape features	32.2%	35.4%
All features	**81.7%**	**80.6%**