A TOOL FOR OBJECT DESCRIPTIVE FEATURE EXTRACTION: APPLICATION TO IMAGE CLASSIFICATION AND MAP UPDATING

L.A. Ruiz*, J.A. Recio, A. Fernández-Sarría, T. Hermosilla

Geo-Environmental Cartography and Remote Sensing Group.
Departamento de Ingeniería Cartográfica, Geodesia y Fotogrametría.
Universidad Politécnica de Valencia. Camino de Vera s/n, 46022 Valencia, Spain.
laruiz@cgf.upv.es

ABSTRACT:

A software tool specifically designed for the extraction of multi-criteria features from image objects is described, as well as an application example. The input data are typically multispectral imagery and a cartographic database to define the limits of the objects, though these limits can also be provided from a different source, such as an automatic image segmentation process. The output is a table with the values of all the features computed for each object, which are presented in different formats, ready to be used as input data in classification tools. Additional interpretive graphs and images can be optionally produced, useful for a better understanding and analysis of features and objects. A complete set of features can be extracted from the images describing spectral, texture and structural properties of the objects. Structural features provide information of the spatial arrangement of different elements in the analyzed object. These are related, for instance, with planting patterns of crops in agricultural parcels. Extraction of texture and structural information is based on the computation of semivariogram, Hough transform, grey level co-occurrence matrix, wavelets transform, etc. Shape features can also be extracted from the limits of the objects. The set of features proposed are applied and evaluated in a real parcel-based classification case, using decision trees combined by means of boosting techniques. The results show the usefulness and potential of the proposed features for semi-automatic land use/land cover mapping and geospatial database updating applications.

1. INTRODUCTION

Classification techniques are used in remote sensing to face a wide range of applications, sometimes introducing additional information related to the spatial distribution of the intensity values of the neighbourhood of the pixels, or using ancillary information and data. Many different methodologies for the classification itself have been tested. 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). A crucial step of a complete classification process is the feature extraction process, and object-based approaches are more flexible than pixel-based to collect and capture properties that permit a better description of it.

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/or homogeneous structure that is easier to understand (Shapiro and Stockman, 2001). These segments have additional spectral and spatial information when compared to single pixels (Blaschke, 2010). In addition to 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.

Different commercial software tools have been made available over the last several years for the feature extraction step, providing a variety of features to describe the properties of the objects and their mutual relations. FETEX 2.0 is an interactive computer program for image automatic object-oriented feature extraction. The software was created by the Geo-Environmental Cartography and Remote Sensing Research Group (CGAT) from the *Universidad Politécnica de Valencia*, it was written in IDL 6.2 and it can be used on ENVI 4.2 or higher versions.

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. The program does not include any segmentation algorithm, but creates the objects according to the limits contained in ESRI shapefiles (shp), allowing for the extraction of spectral, textural, shape and structural features from images. For each object, the output is a feature vector to be used with the selected classifier. Besides the classification of the database objects, the information obtained with FETEX 2.0 can be used as ancillary information in agricultural inventories: 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. This software has been successfully applied in the feature extraction phase in several land use/land cover geospatial database updating processes (Ruiz et al., 2009). Interested users are most likely to be among the cartographic research community and official mapping agencies devoted to updating and maintaining large land use/land cover databases. A limited version of FETEX 2.0 is available at the CGAT group website (http://cgat.webs.upv.es).

2. SOFTWARE DESCRIPTION

The graphic user interface of FETEX 2.0 is a window menu divided in several basic areas: Input files, selection of object-oriented features and parameters, output files, and ancillary output (Figure 1a). In the following sections these areas are described, enphasizing the different types of features calculated at object level.

2.1 Input files

The Image and Shape buttons allow for the selection of the image to be analyzed, and the shapefile containing the limits of the cartographic objects. Image formats supported by FETEX 2.0 are those supported by ENVI (GeoTIFF, ENVI binary, ERDAS img, JPG2000, etc.). The image and the shapefile should be in the same spatial reference system.

The database associated to the shapefile must contain a field with the identifiers of the parcels or polygons to be processed. In addition to the polygons defined in a shapefile, the same information in ENVI Vector File format (.evf) is required. When working with large datasets, an ASCII file containing the paths of several images and shapefile can be provided instead proceeding file by file. The images must have the same pixel size, number and order of bands, and reference system. The shapefile must have the same structure of attributes. In the case that a parcel (object) shares the image information in several image files, FETEX 2.0 will internally collect information about the images, building a mosaic and extracting the final descriptive features from this new composed image.

Two parameters related to the input files can be fixed: *Minimum parcel size*, controling the minimum area of a polygon to be processed, avoiding very small polygons that may difficult a correct characterization; and *Parcel perimeter buffer*, which is used to reject the peripheral pixels in the analysis, reducing the risk to include pixels that are external to the object due to geo-referencing errors or misregistration between the database and the image. The values of the associated droplist represent the thickness of the rejecting buffer in pixels.

2.2 Object-oriented features

Figure 1b shows the graphic user interface of FETEX 2.0 for the selection of the specific features that can be obtained from the different feature groups that are described in the following sections, as well as the methodological parameters involved.

2.2.1 Spectral features

Spectral features provide information about the spectral response of objects, as captured by the sensors. 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 could 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 are calculated.

2.2.2 Texture features

The texture on an image is related to 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. Here, each texture feature value is referred to and extracted from a particular object. The simplest manner to characterize texture is based on the first order histogram features. FETEX 2.0 includes kurtosis and skewness. Seven features proposed by Haralick et al. (1973), based on the grey level co-occurence matrix (GLCM) can be extracted: 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.
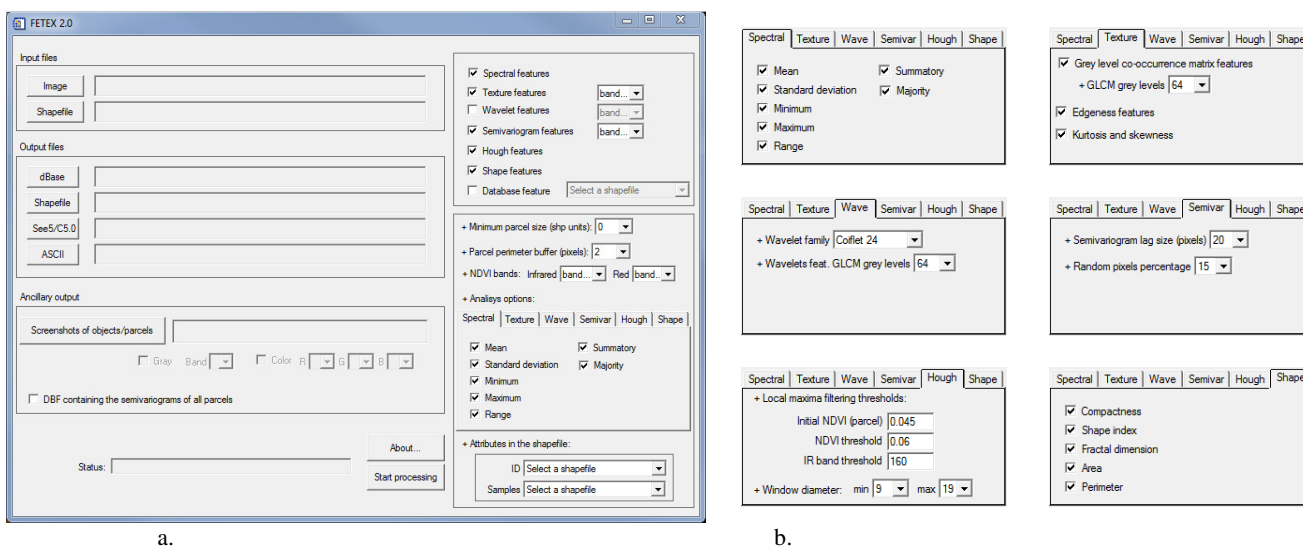

Figure 1. (a) FETEX 2.0 interface and (b) menus of feature groups and parameters.

The *edgeness factor* (Sutton and Hall, 1972) represents the density of edges present in a neighbourhood, having a good performance in different landscape classification problems (Ruiz et al., 2004). The mean and the standard deviation of the *edgeness factor* has been included in the program.

2.2.3 Wavelet-based texture features

The use of the wavelet transform for texture analysis was first proposed by Mallat (1989). An advantage of wavelet decomposition is that 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:

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

where s is a parameter defining 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:

$$Wf(s,u) = \int_\Re f(x)\frac{1}{\sqrt{s}}\psi^*\left(\frac{x-u}{s}\right)dx \qquad (2)$$

The extension to a 2-D discrete function is 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. In the multiresolution analysis, the inverse transform is applied to the fluctuations, and three reconstructed images, or details, are obtained: horizontal, vertical and diagonal.

Seven families of wavelet functions (Haar, Daubechies, Coiflet, Meyer, Symlet, Shannon and Battle-Lemarié) can be applied over the image objects using FETEX 2.0. Defining the support of a wavelet function as the smallest closed interval, outside of which the function is zero (Bultheel, 1995), different supports are available 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. In order to reduce this effect 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.

2.2.4 Structural features

They provide information of the spatial arrangement of the elements or primitives in the object, in terms of randomness or regularity of their distribution. This is the case of alignments or regular patterns that are present in different man-made landscapes, such as the planting patterns of crops and trees in agricultural plots. The identification of regular planting patterns can be particularly useful in agricultural classification, as reported by several authors (Helmholz et al., 2007; Ruiz et al., 2009; Recio, 2009; Hermosilla et al., 2010). Structural features computed in FETEX 2.0 are based on the semivariogram and the Hough transform. Both are described in Ruiz et al. (2007). Additionally, an exhaustive description and interpretation of the features derived from the experimental semivariogram can be found in Balaguer et al. (2010).

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, being a particularly suitable tool in the characterization of regular patterns. The semivariogram has been widely used in digital image processing and remote sensing (Carr, 1996; Woodcock et al., 1988; and many others), in order to extract different features from images, computed in a window around a pixel in order to perform classification. FETEX 2.0 computes, for each object, the mean of the semivariograms calculated in six different directions, ranging from 0º to 150º with a step of 30º. 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 follow a regular pattern, the semivariogram has a cyclic behaviour, and it is known as hole-effect semivariogram (Pyrcz and Deutsch, 2003). Figure 2 shows the experimental semivariogram curves of two parcels with different land uses.
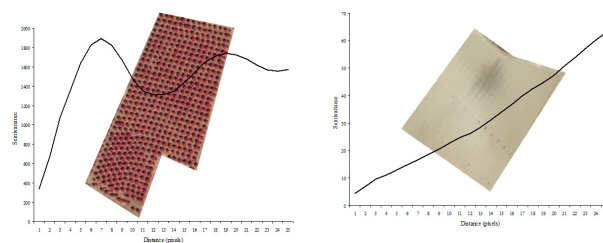

Figure 2. Semivariogram graphs of two parcels with different land uses.

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).

Once the information about global regularity of the parcel is extracted from the semivariogram analysis, the plantation pattern can be more profoundly analysed. For this purpose, a variety of features based on the Hough transform are included in FETEX 2.0. As a first step, the trees are located using the local maximum filtering (LMF) method (Gourgeon, 1999) applied over NDVI images obtained 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 size of the kernel 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. A NDVI bands droplist on the graphic user interface of FETEX allows for the selection of the two image bands required for computing the NDVI: the IR and red bands.

From the binary image obtained, main tree alignments are extracted and characterized applying the Hough transform (Hough, 1962). Structural information derived from the Hough transform has been used for automatic classification and characterization of agricultural landscapes. 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 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. Polar space can be grouped into a histogram of frequencies for all directions ranging from 0º to 179º. When there is some regularity in their spatial arrangement, two histogram maxima appear, corresponding to the principal directions or alignments of trees in the parcel. A set of features related to the regularity in the distribution of trees are extracted from this transformation and the histogram of orientations: 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.

Figure 3 shows an example of a parcel with trees arranged following a regular pattern, the NDVI image with the local maxima superimposed representing the location of trees, the orientations of the two principal alignments and the distance between tree rows (d1 and d2).
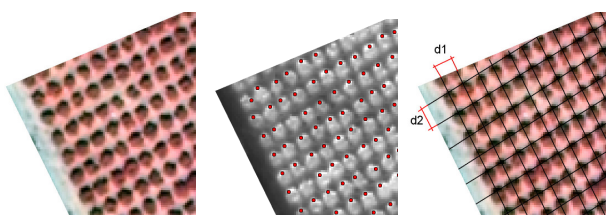

Figure 3. Location of trees on the NDVI image and automatic extraction of distances between trees inside each object

2.2.5 Shape features

The shape features computed in FETEX 2.0 are mainly based on ratios between the area and the perimeter of the objects. These descriptors, extracted directly from the polygons of the objects contained in the database can help to distinguish and identify different elements with particular shapes, such as roads, rivers, circular plots, etc. In addition to the area and perimeter of each object, the features available in the application are: the compactness (Bogaert et al., 2000), shape index and fractal dimension (Krummel et al., 1987).

2.2.6 Ancillary data

Sometimes, qualitative information can be included as descriptive features in a subsequent classification process. Some studies (Rogan et al., 2003; Recio et al., 2009) have shown that the combination of the previous land use of the parcels contained in an old database with spectral features may increase the overall accuracy of the classification. Additionally, some other discrete information, such as soil type and composition (Huang and Jensen, 1997), irrigation type, etc. can be useful to better describe the parcels or polygons. If this information is included in the spatial geodatabase as an input in the program, it can also be added as an output to the descriptive feature vector of each object. If the *Database feature* option button on the graphic user interface is enabled, the field of the shapefile database containing the descriptive feature must be selected from the adjoining drop-down list. Any other georreferenced information in raster format can also be added as additional bands to extract information and characterize the objects, such as digital terrain models (elevation, slope or aspect), distance maps, results of a per-pixel classification, etc.

2.3 Output files

As a result of processing the image for object information extraction, an output table containing the values of the 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 C5.0 algorithm, which is the latest version of the algorithms ID3 and C4.5 developed by Quinlan (1993).

2.4 Ancillary output

FETEX 2.0 provides the option of generating a set of screenshots, helpful for the interpretation of the results (Figure 4). The set of screenshots obtained for every object includes a color or grey level image of the object and the wavelet details, grey level image files of the GLCM of both, the original image and the wavelet details image, the semivariogram curve of the image object, a binary image of the tree locations automatically detected, the graph of the Hough transform, and the binary image of the tree alignments. Additionally, a dbf file containing the semivariogram for each analyzed object can be generated.

3. APPLICATION

The data used in this study were 0.5 m/pixel resolution digital aerial orthophotographs, acquired in August 2005 with a Digital Mapping Camera (DMC) sensor. The ancillary data come from a cadastral geospatial database, and are composed of the cartographic boundaries of the cadastral parcels and their attributes: cadastral identifier, area, land use, etc. Eleven land use classes were defined, and a total of 1440 evaluation parcels were selected and carefully photointerpreted for evaluation, independent from the training set. Classification was performed using the variables computed using FETEX 2.0, and decision trees were built using the C5.0 algorithm and following a boosting process. Classification assessment was based on the analysis of the confusion matrix (Congalton, 1991), by comparing the class assigned to each evaluation sample with the reference information. Table 1 shows the evaluation matrix, with an overall accuracy of 93% and user and producer accuracies ranging from 83% to 99%. Considering an 11 classes problem, the methodology used, based on the automatic

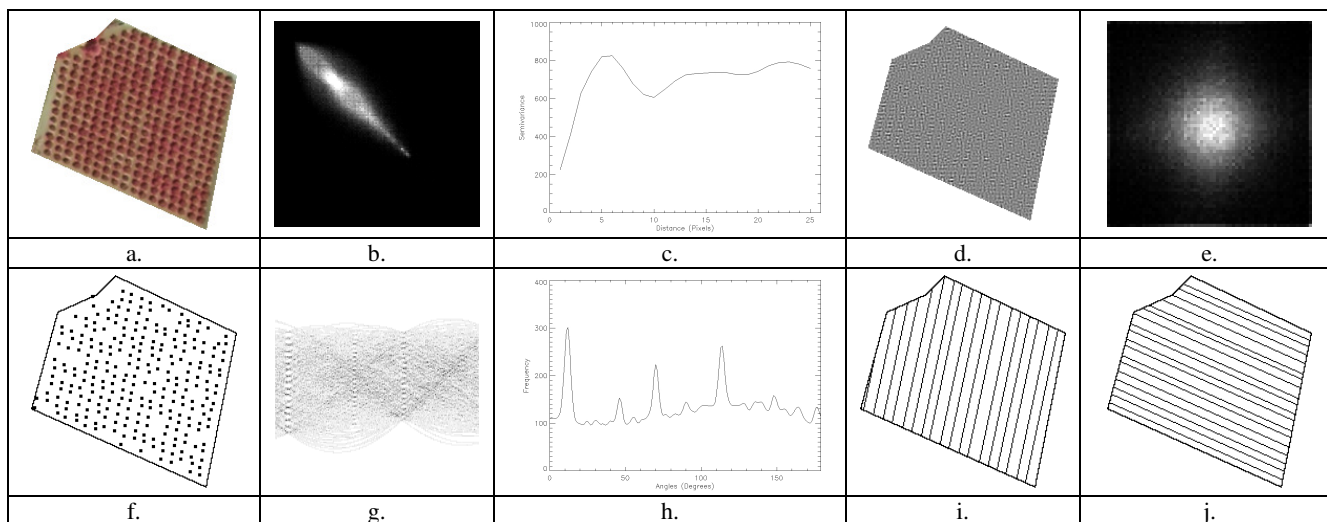|				
a.	b.	c.	d.	e.
f.	g.	h.	i.	j.

Figure 4. Screenshots obtained with FETEX 2.0. for a parcel: color level image of the object (a) and grey level image of the wavelet details (d), image representations of the GLCM of both, the original image (b)and the wavelet details(e); semivariogram curve of the image object (c); binary image of the tree locations (f); Hough transform (g) and histogram of directions (h); and binary image of the tree alignments detected (i) and (j).

computation of features extracted with FETEX, provides encouraging results, suggesting the adequacy of the proposed object-oriented analysis methods for application in land use/land cover database classification and updating based on high-resolution remotely sensed imagery.

4. CONCLUSIONS

FETEX 2.0, a software tool for the extraction of a wide range of features from images and databases has been described, and its performance has been illustrated using a data set and a real classification problem. This 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 can be extracted from lidar data, complementing the current information. New features derived from sub-objects, and from their contextual relations, can help to improve the description of the object and to resolve more efficiently different classification problems. This tool has a potential for application in land use database updating.

		Reference											
		Irrigated crops	Arable lands	Industrial building	Single house	Urban building	Forest	Citrus groves	Carob-trees	Shrublands	Beach	Roads	Total	User's accuracy
Classified as	Irrigated crops	105						1		14			120	87.5
	Arable lands		111								3		114	97.4
	Industrial building			106		5			1		2	1	115	92.2
	Single house				114	3			1	2			120	95
	Urban building			9	2	112			4				127	88.2
	Forest				1		119		1	1			122	97.5
	Citrus groves				1			232		2		2	237	97.9
	Carob-trees			3	2			2	112	1		2	122	91.8
	Shrublands	15					1	5	1	100			122	82
	Beach		8	2							115	1	126	91.3
	Roads		1									114	115	99.1
	Total	120	120	120	120	120	120	240	120	120	120	120	1440	
	Producer's accuracy	87.5	92.5	88.3	95	93.3	99.2	96.7	93.3	83.3	95.8	95		**93%**

Table 1. Evaluation matrix of the classification.

REFERENCES

Balaguer, A., Ruiz, L.A., Hermosilla, T., Recio, J.A., 2010. Definition of a comprehensive set of texture semivariogram features and their evaluation for object-oriented image classification. *Computers & Geosciences*, 36(2), pp. 231-240.

Blaschke, T., 2010. Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, 65(1), pp. 2-16.

Bogaert, J., Rousseau, R., Hecke, P. V., Impens, I., 2000. Alternative area-perimeter ratios for measurement of 2D shape compactness of habitats. *Applied Mathematics and Computation*, 111(1), pp. 71-85.

Bultheel, A., 1995. Learning to swim in a sea of wavelets. *Bulletin of the Belgian Mathematical Society*, 2(1), pp. 1-46.

Carr, J.R., 1996. Spectral and textural classification of single and multiple band digital images. *Computers & Geosciences*, 22(8), pp. 849-865.

Congalton, R., 1991. A review of assessing the accuracy of classications of remotely sensed data. *Remote Sensing of Environment*, 37(1), pp. 35-46.

Fernández-Sarría, A., 2007. Study of techniques based on the wavelet transform and optimization of its parameters for texture classification of digital images. PhD Dissertation, Universidad Politécnica de Valencia, Spain, 247 pp.

Gougeon, F., 1999. Automatic individual tree crown delineation using a valley-following algorithm and a rule-based system. In: *Proceedings International Forum of Automated Interpretation of High Spatial Resolution Digital Imagery for Forestry*, Victoria, BC, pp. 11–23.

Haralick, R.M., Shanmugam, K., Dinstein, I., 1973. Texture features for image classification. *IEEE Transactions on Systems, Man and Cybernetics*, 3(6), pp. 610-622.

Hay, G.J., Castilla, G., 2006. Object-based image analysis: strengths, weakness, opportunities and threats (SWOT). *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXVI - 4/C42 on CD.

Helmholz, P., Gerke, M., Heipke, C., 2007. Automatic discrimination of farmland types using Ikonos imagery. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXVI-3/W49A, pp. 81-86.

Hermosilla, T., Díaz-Manso, J.M., Ruiz, L.A., Recio, J.A., Fernández-Sarría, A., Ferradáns-Nogueira, P., 2010. Parcel-based image classification as a decision-making supporting tool for the Land Bank of Galicia (Spain). *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXVIII-4-8-2-W9, pp. 40-45.

Hough, P.V.C., 1962. Methods and means for recognizing complex patterns, U.S. Patent No. 3069654.

Huang, X., Jensen, J.R., 1997. A machine-learning approach to automated knowledge-base building for remote sensing image analysis with GIS data. *Photogrammetric Engineering & Remote Sensing*, 63(10), pp. 1185-1194.

Krummel, J. R., Gardner, R. H., Sugihara, G., O'Neill, V., Coleman, P. R., 1987. Landscape patterns in a disturbed environment. *OIKOS*, 48(3), pp. 321-324.

Mallat, S.G., 1989. A theory of multiresolution signal decomposition: The wavelet representation. *IEEE transactions on pattern analysis and machine intelligence*, 11(7), pp. 674-693.

Pyrcz, M. J., Deutsch, C. V., 2003. The whole story on the hole effect. In: Searston, S. (Eds.) *Geostatistical Association of Australasia Newsletter*, 18.

Quinlan, J.R., 1993. C4.5, Programs for Machine Learning, Morgan Kaufmann Publishing, San Mateo, 302 pp.

Recio, J.A., 2009. Feature extraction techniques and object-oriented image classification applied to land use/land cover databases updating. PhD Dissertation. Universidad Politécnica de Valencia, Spain, 289 pp.

Recio, J.A., Hermosilla, T., Ruiz, L.A., Fernández-Sarría, A., 2009. Analysis of the addition of qualitative ancillary data on parcel-based image classification. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXVIII-1-4-7/W5 on CD.

Rogan, J., Miller, J., Stow, D., Frankling, J., Levien, L., Fischer, C., 2003. Land cover change mapping in California using classification trees with multitemporal Landsat TM and ancillary data. *Photogrammetric Engineering & Remote Sensing*, 69(7), pp. 793-804.

Ruiz, L.A, Fernández-Sarría, A., Recio, J.A., 2004. Texture feature extraction for classification of remote sensing data using wavelet decomposition: A comparative study. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXV- B4, pp. 1109-1114.

Ruiz, L.A., Recio, J.A., Hermosilla, T., 2007. Methods for automatic extraction of regularity patterns and its application to object-oriented image classification. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXVI-3/W49A, pp. 117-121.

Ruiz, L.A., Recio, J.A, Hermosilla, T., Fernández-Sarría, A., 2009. Identification of agricultural and land cover database changes using object-oriented classification techniques. In: *Proceedings 33rd International Symposium on Remote Sensing of Environment*, Stresa, Italy, on CD.

Shapiro, L.G., Stockman, G.C., 2001. *Computer Vision*, Prentice-Hall, New Jersey, 580 pp.

Sutton, R.N., Hall, E.L., 1972. Texture measures for automatic classification of pulmonary disease. *IEEE Transactions on Computers*, 21(7), pp. 667-676.

Woodcock, C.E., Strahler, A.H., Jupp, D.L.B., 1988. The use of variograms in remote sensing I: Scene models and simulated images. *Remote Sensing of Environment*, 25(3), pp. 323-348.

Wulder, M., Niemann, K.O., Goodenough, G.D., 2000. Local maximum filtering for the extraction of tree locations and basal area from high spatial resolution imagery. *Remote Sensing of Environment*, 73 (1), pp. 103-114.