Use of Gabor filters for texture classification of digital images

Jorge A. Recio Recio,
Luis A. Ruiz Fernández,
Alfonso Fernández-Sarriá

Universidad Politécnica de Valencia
Dpto. de Ingeniería Cartográfica, Geodesia y Fotogrametría
Camí de Vera, s/nº - 46022 Valencia
jrecio@cgf.upv.es

ABSTRACT

In this article various methodologies, based on the use of Gabor filters, are described and analysed for the extraction of texture features and the subsequent classification of aerial and satellite digital images. Images of urban, forest and agricultural areas were used, where the complexity of the terrain and the differences in vegetation density require the consideration of the existing texture features as a base for elaborating land use cartography. The use of Gabor filters is driven by the potential they have to isolate texture according to particular frequencies and orientations. The parameters that define a Gabor filter are its frequency, standard deviation and orientation. By varying these parameters, a filter bank is obtained that covers the frequency domain almost completely.

Several alternatives have been studied for the application of Gabor filters: (a) the use of complete filter banks; (b) the sum of the filters of equal frequency; and (c) the selection of those filters that minimise, a priori, the classification error.

From the application of filters in each of the three methods, a group of images is obtained that allow for the numeric quantification of textures in the image. The evaluation of the classification results shows that combining these textural variables with the multispectral information permits us to characterize the existing regions in the territory with more precision, using supervised digital image classification techniques.

Key Words: Image classification, Gabor filters, multichannel filtering, texture analysis.

Física de la Tierra
2005, 17 47-59

ISSN: 0214-4557

1 INTRODUCTION

In a digital image, the *texture* refers to a group of properties or features that describe the spatial distribution of the grey levels that correspond to the pixels of a particular region. Their characterisation is especially relevant in certain terrain classification processes using aerial and satellite images, particularly in spectrally heterogeneous areas, where assigning a class to each pixel by analysing only the spectral response is not sufficient, and therefore is necessary to take into account the spatial context of the pixel. Many tree crops are a clear example of how the spectral information present in the image is not the most appropriate characteristic used for a correct classification. Instead, the identification of the geometric patterns that trees form according to a particular plantation distance is more relevant.

There are many texture analysis techniques that are used for the extraction of features: statistical methods (grey level co-occurrence matrix, grey level difference vector), filtering techniques (energy filters, Gabor filters), wavelet decomposition-based methods, etc.

In this study, we focus on analysing some of the Gabor filter application techniques for the characterisation of textures that are present in very different environments: urban areas with very diverse types of construction, dry and irrigated agricultural areas, and forest areas with a great deal of variety in the type and density of vegetation. The main objective of this research is to analyse different application methodologies of the Gabor filters as an instrument for the texture characterisation of satellite digital images, in order to obtain thematic information from a single panchromatic band.

2 MATERIALS AND AREA OF STUDY

The tests were performed using two images containing very different landscapes, combining urban, agricultural and forest areas. In these spectrally heterogeneous landscapes, it is necessary to consider the existing texture features before elaborating the land use cartography.

The characteristics of the areas and images used are briefly described below:

a) *Espadán*: It is a mountain range of the same name located in the southern part of the province of *Castellón*, near the coast. Forests (*Pinus halepensis* y *Quercus suber*), shrubs, olive groves and rocky areas predominate. The classes were defined as: *dense forest*, *medium-density forest*, *shrub-forest*, *shrubs*, *bare soil with scattered trees*, *bare soil with shrubs*, and *olive grove*. A mosaic, composed of 9 sub-areas, was created using 1m resolution aerial orthoimages (Fig. 1a).

b) *Valencia*: An area situated in the northern part of the city of *Valencia* that includes several municipalities of the *l'Horta Nord* region. The classes taken into account are: "*Old urban*", which represents the urban centres with irregular edification; "*ensanche*", areas of recent and planned urban expansion; "*residential areas with trees*", residential areas near the city with embedded forest areas; "*industrial areas*"; "*citrus orchards*"; and "*horticulture crops*", horticultural areas without trees and with some scattered buildings. A panchromatic image from the Quickbird satellite was used. Given the characteristics of urban textures, it was resampled to a resolution of 5m (Fig. 1b).

(a) (b)

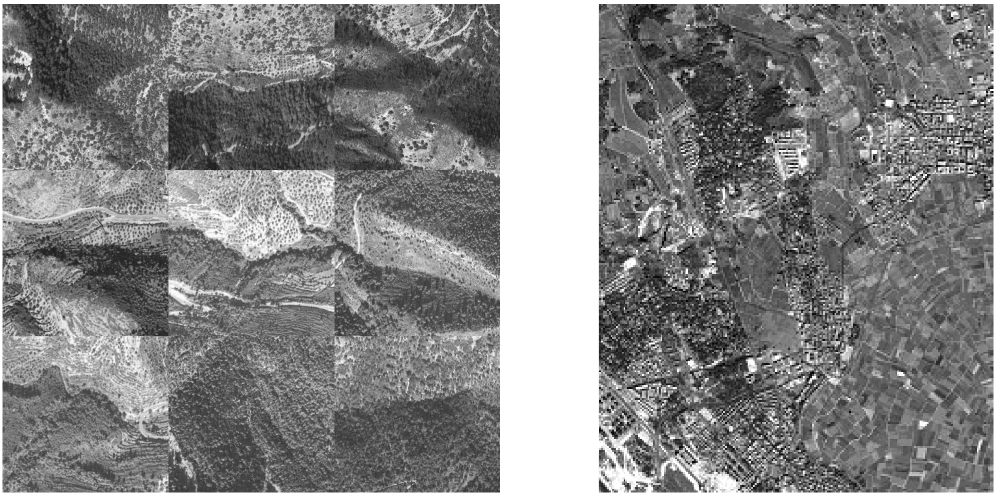

Figure 1. Working images. a) *Espadán* Mountain Range b) Northern *Valencia.*

3. METHODOLOGY

The multichannel filter is an effective method in the field of texture analysis. The filter banks have the particular characteristic of decomposing an image into texture features, which can be used to classify each pixel of the image in a type of land use. The multichannel filtering process imitates the characteristics of the human visual system, which decomposes the image on the retina into several filtered images, each of which has variations in intensity within a limited range of frequencies and orientations (Jain & Farrokhnia 1991). A Gabor filter bank is formed by a group of Gaussian filters that cover the frequency domain with different radial frequencies and orientations (Randen 1997). Therefore, the textures are characterised by their responses to the filters, each of these filters is designed for a particular frequency and orientation (Idrissa et al. 2002).

Texture analysis methods using Gabor filters can be grouped into two categories (Clausi et al. 2000): Supervised and non-supervised methods. Supervised methods use filters with parameters selected from the texture features to be identified. Bovik (1991) selected the most adequate filters, based on a prior knowledge of the image textures. The non-supervised methods are more attractive, as they generate a complete filter bank, and do not require the user to precisely define the parameters that unequivocally identify a texture.

In the spatial domain, a Gabor filter consists of a Gaussian function modulated by a sinusoidal curve

$$h(x,y) = \frac{1}{2\pi\sigma_g^2} \cdot \exp[-\frac{(x^2+y^2)}{2\sigma_g^2}] \cdot \exp(j2\pi F(x\cos\theta + ysen\theta))$$

where σ_g determines the spatial extension of the filter in the spatial domain (Fig. 2).

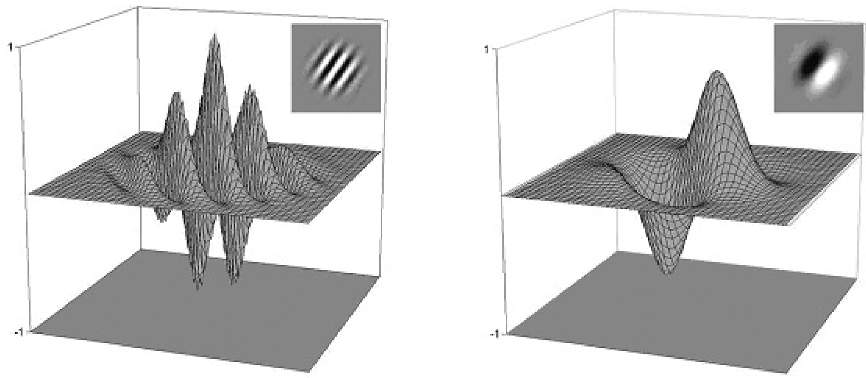

Figure 2. 3D grey level representation of a Gabor filter. Real part (left) and imaginary part (right).

In the frequency domain, the Gabor function is a Gaussian curve centred at the coordinates (*Fcos*υ, *Fsen*υ) (Bodnarova et al. 2002). The Fourier transform of the Gabor function is represented by the expression:

$$H(u,v) = \exp[-2\pi^2\sigma_g^2((u - F\cos\theta)^2 + (v - Fsen\theta)^2)]$$

The parameters that define each of the Gabor filters are: the F radial frequency where the filter is centred in the frequency domain, the standard deviation of the Gaussian curve, that determines the extension of the filter in the spatial domain, and the orientation with respect to the abscissa axis. For the purpose of simplicity, we assume that the Gaussian curve is symmetrical.

The filter bank was carried out with six orientations υ = (0º, 30º, 60º, 90º, 120º and 150º) and three radial frequency values: F = (0.3536, 0.1768 and 0.0884). This leaves us with a total of 18 filters that cover the frequency domain. Different standard deviation values of the Gaussian curve were tested (Chen, et al.1999), those being the two sets of three values used in the study σ_g = (1.91, 3.82 and 7.63) and σ_g = (2.86, 5.73 and 11.44) (Fig. 3a).

(a) (b)

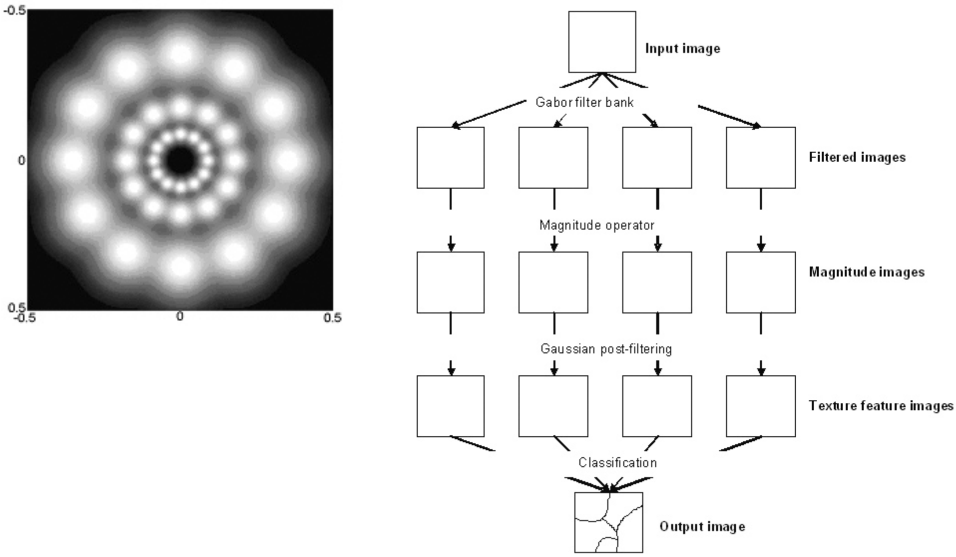

Figure 3. a) Gabor filter bank in the frequency domain, with 6 orientations and 3 radial frequency values. b) Diagram of the procedure followed for the extraction of texture variables and classification

Once the filter bank was designed, the methodological procedure followed for the extraction of texture variables and later image classification was the following (Fig. 3b): The filter bank was applied to the input image and the magnitude of the filtered images was obtained. Next, a Gaussian low-pass filter was applied to this magnitude image, with the purpose of reducing its variance and, consequently, reducing the classification error. Several tests with three different standard deviation values of the post-processing Gaussian values (σ_p = 2, 5 and 10) were carried out in order to analyse the influence of this filter in the classification process. The images resulting from this filtering process served as variables or input texture bands in a supervised classification process using the maximum likelihood method.

3.1. Alternatives for the use of Gabor filters

Three alternative methodologies for applying Gabor filters were tested to compare their efficiency.

A) Use of complete filter banks

It consists of defining a large group of filters with certain parameters that allow the frequency plane to be covered effectively. A large number of texture features are generated, which improve the classification process, but some of them will give redundant information. A large part of the frequencies in the image are isolated but, at the same time, frequency images are generated that are not represented in the image.

The filter banks defined are composed of 18 filters that correspond to the combination of six orientations and three frequencies. Two banks or groups of filters were created by varying the standard deviations of the Gaussian curves corresponding to the three frequencies. The two sets of three values used are σ_g = (1.91, 3.82 and 7.63) and σ_g = (2.86, 5.73 and 11.44).

B) Sum of the images obtained through filters of a same frequency

The orientation of the texture is a property whose analysis is not generally of interest for land use classification of images, different from what occurs in other fields. Thus, the classification results obtained using the sum of the output images from filtering with the 6 filters corresponding to a determined frequency were tested, so discarding the information related to texture orientation.

The information included in the 18 features, coming from the application of a complete filter bank, is summarised in three images that correspond to each of the frequencies used in the filters:

$$B_{0.3536} = B_{0.3536}^{0°} + B_{0.3536}^{30°} + B_{0.3536}^{60°} + B_{0.3536}^{90°} + B_{0.3536}^{120°} + B_{0.3536}^{150°}$$

C) Selection of the filters that minimise the segmentation error

As an alternative to using a complete Gabor filter bank, and in order to reduce the total number of bands used in the classification, the algorithm proposed by Weldon and Higgins (1998) to select those filters that give a higher degree of separability between the training samples of the classifier was used. With this method, we attempt to determine which are the most adequate filters for the discrimination of the textures in the image, allowing us to discard those that do not offer relevant information for classification or that are redundant. In this way, the volume of data used in the classification is reduced without causing a decline in its overall accuracy.

The first step is to define a group of filters that cover the frequency domain with multiple resolutions. The parameters used for this are the same as those used in Gabor banks (described previously) and, therefore, the results obtained using the three variables are immediately comparable. The parameters that define each of these filters are $\Phi_j = (F_j, \upsilon_j, \sigma_{gj}, \sigma_{pj})$.

Next, each of these filters is applied to small sample images that are representative of the classes or textures present in the image, which have been previously defined. The segmentation error for each of the filters was calculated using these samples. For the group of filters $\Theta_k = [\Phi_1, \Phi_2, \ldots, \Phi_k]$, the *a priori* segmentation error was calculated using the expression:

$$\xi_t(\Theta_k) \approx \sum_{\alpha=1}^{N-1} \sum_{\beta=\alpha+1}^{N} \frac{(P_\alpha P_\beta)^{1/2}}{N-1} e^{-B(t_\alpha, t_\beta, \Theta_k)} + \frac{1}{k} \sum_{j=1}^{k} \frac{2(N)(\sigma_g^2 + \sigma_p^2)}{N^2}$$

where P_α and P_β are the *a priori* probabilities of the t_α and t_β textures in the image. N x N are the dimensions of the image and B $(t_\alpha, t_\beta, \Theta_k)$ is the Battacharyya distance between textures t_α and t_b for a given group of filters Θ_k.

The calculation of the segmentation error obtained for each of the filters allows for the selection of the filter that has minimum error. Once the first filter is chosen, the same procedure is followed to identify a second filter that, combined with the one chosen in the previous step, minimises the segmentation error.

This step is repeated until the desired number of filters has been selected or until a segmentation error lower than that specified by the user is obtained.

The evaluation of the three methods or alternatives described and the six parameter combinations was carried out by analysing the overall accuracy after classifying the images resulting from each of the 18 possible combinations between them, using the maximum likelihood method. The overall accuracy of the classifications is obtained by comparing the class assigned to a group of pixels with the real class determined by photointerpretation. The six combinations of parameters tested are summarised in Table 1.

Table 1. Combinations of parameters tested.

	σ_g =(1.91,3.82,7.63)	σ_g =(2.86,5.73,11.44)
$\sigma_p = 2$	CP 1	CP 4
$\sigma_p = 5$	CP 2	CP 5
$\sigma_p = 10$	CP 3	CP 6

3.2. Combination of Gabor filters with other texture variables

Traditionally, the texture analysis methods based on statistical indices calculated from the neighbourhood of each pixel have been used in a standard manner. There are two main groups, the first order methods, directly extracted from the histogram, and the second order methods, that are calculated from the grey level co-occurrence matrix (GLCM) and were initially proposed by Haralick (1973). In previous studies (Ruiz et al. 2004), an increase in the efficiency of texture classification has been shown by combining texture variables based on filtering methods with statistical variables. Considering this, and in order to study their complementarity, classifications using Gabor filters together with 8 variables derived from the GLCM were also tested. The Gabor filters used in this test were created with the combination of the CP5 parameters (table 1) and using method B, that is, with only three variables.

4. RESULTS

In Fig. 4, the overall accuracy rates of the classifications corresponding to the image of the urban area (*Valencia*) are shown. Most of the accuracy values obtained in the 18 classifications tested range between 65% and 70%.

In all cases, the use of the complete filter bank (method A) offers the best accuracy results. With method B, the probabilities obtained are slightly lower, although the advantage of working with only three bands means an important reduction in the number of variables to be used in the classification, and confirms the initial hypothesis of the limited influence that orientation has on natural textures.

In this area, with method C, worse results were obtained than with the other methods tested in all of the cases. Although it allows for a reduction in the number of variables or features, there are always more than three.

On the other hand, the use of the Gaussian post-processing filter helps lessen the variability in the image and increases the reliability of the classifications.

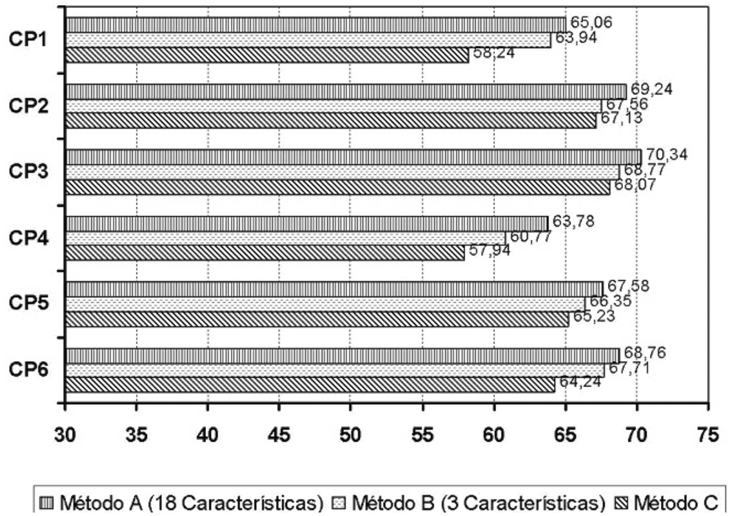

Figure 4. Overall accuracy scores for the classifications of the urban area image (*Valencia*)

The results of the image of the forest area (*Espadán*) (Fig. 5) confirm some of the results shown for the urban area.

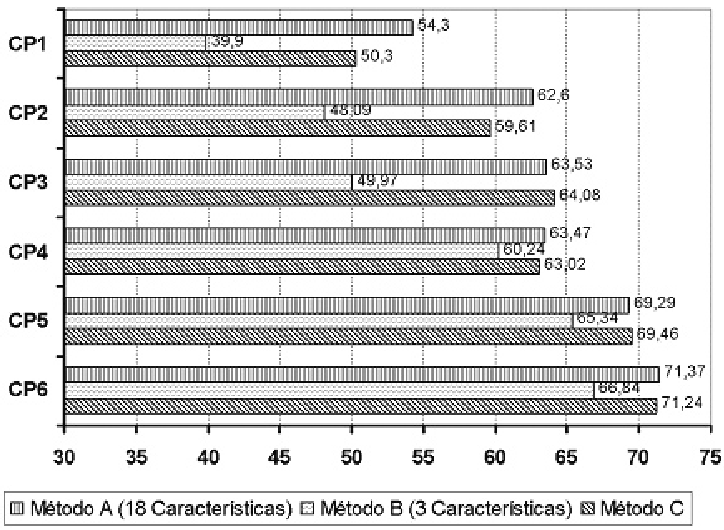

Figure 5. Overall accuracy scores for the classifications of the forest area image (*Espadán*).

As in the urban area, the use of the complete filter bank offers the highest levels of reliability in the classification.

The Gaussian post-processing filter is efficient in homogenising the output images resulting from the application of the Gabor filters. It is observed that better results are obtained when the standard deviations of the filters are raised.

In this area, the method based on the selection of the filters that minimise segmentation error (method C) is more effective than the method that combines filters of the same frequency (method B), unlike what was found in urban areas. It must be taken into consideration that in method C, only 7 variables or bands are used in the sixth combination of parameters (notation CP6 in Fig. 5), as opposed to the 18 variables used in method A.

Method B is not very effective, especially when it is used with smaller parameters.

Method C is quite effective with this image, as the accuracy results are very similar to those calculated with method A, allowing for a significant reduction in the number of variables.

Fig. 6 shows an example of the results obtained, after classifying the features obtained using method A and the combination of the CP6 parameters (see table 1).

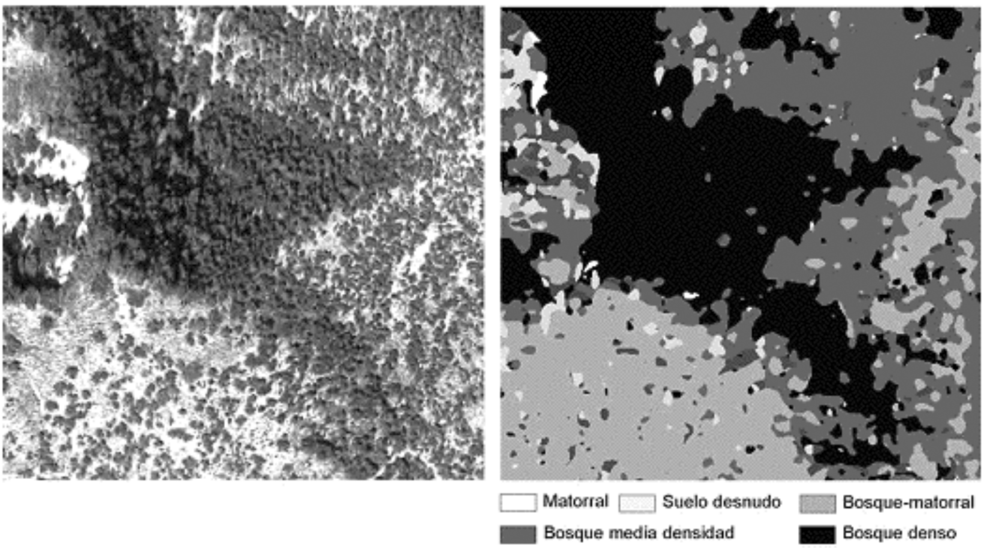

Figure 6. Classification detail of the *Espadán* image a) Original image b) Classified image.

In the combined testing, using Gabor filters and the 8 variables derived from the GLCM, there are significant differences in the performance of each of the two methods, depending on the area of study and, as a result, on the type of textures that are to be differentiated. In the urban textures, the best results were obtained using the method based on the GLCM, while in the forest textures the results of both methods are similar. However, by combining the two types of variables (GLCM + Gabor filters), the accuracy significantly increases in both of the areas studied (table 2).

Table 2. Overall accuracy scores for the texture methods compared.

	GLCM	Gabor F.	GLCM+ Gabor F.
Valencia	84.25	66.35	86.46
Espadán	65.97	65.34	71.03

After analysing the results, in order to obtain satisfactory results in the classification of complex images, the necessity of combining the different methods that exist becomes clear. It is interesting to emphasise that, with only 3 variables, the Gabor filters allow for the synthesis of most of the texture information. In Fig. 7, an example of the image from *Valencia* classified using the characteristics extracted from the GLCM and the Gabor filters is shown.

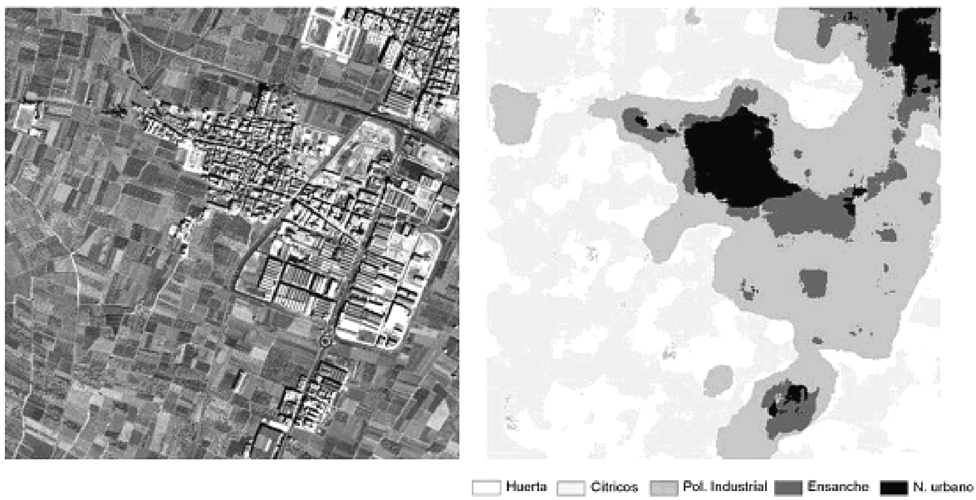

Figure 7. Classification detail of the *Valencia* image a) Original image b) Classified image

5. CONCLUSIONS

The results confirm the ability of the Gabor filters to obtain texture features using panchromatic images. Additionally, the combination of this type of filtration with texture variables extracted through statistical methods based on the gray level co-occurrence matrix allows us to increase the reliability of the classifications.

Of the three methods analysed, the use of the complete Gabor filter bank has shown to be the most effective, and, although it is the method that requires less computational effort for its execution, this is not true for the classifying of information resulting from its application.

The method of selecting filters based on the Battacharyya distance has not been shown to be very effective in reducing the number of variables. However, it must be noted that the number of filters with which the selection was made was very small compared to the exhaustive group of possible filters that Weldon and Higgins (1998) define. The selection of the most adequate filters requires a high degree of computational effort, as each of the samples of the different classes must be filtered with all filters and the segmentation error must be calculated repeatedly for each of the possible filter combinations. On the other hand, in those cases in which the orientation is not a defining parameter of the texture, it is possible to reduce the number of texture features by using the sum of the images obtained with filters of the same frequency.

To summarise, thematic landscape information can be almost automatically obtained, from only one band or grey level image, using these analysis methods. Additionally, by including spectral information, the image classification results can be greatly improved, as the spatial information offered by the texture variables complements the information of the multispectral images. Lastly, one of the aspects that should be improved is the treatment of classification errors that appear in the transition areas of adjoining textures, caused primarily by the fact that the filters are applied in neighbourhoods.

6. ACKNOWLEDGEMENTS

We would like to thank the Spanish Ministry of Science and Technology and the FEDER for the financial support within the frame of the research projects REN2003-04998 and BTE2002-04552.

7. REFERENCES

BODNAROVA, A., M. BENNAMOUN & S. LATHAM, 2002. Optimal Gabor filters for textile flaw detection. *Pattern Recognition.* 35: 2973-2991.

BOVIC, A.C., 1991. Analysis of multichannel narrow-band filters for image texture segmentation. *IEEE Transactions on signal processing. 39(9) 2025-2043.*

CHEN, C.C. & CC. CHEN, 1999. Filtering methods for texture discrimination. *Pattern Recognition Letters.* 20: 783-790.

CLAUSI, D.A & M.E. JERNIGAN, 2000. Designing Gabor filters for optimal texture separability. *Pattern Recognition.* 33: 1835-1849.

HARALICK, R., K. SHANMUGAM & I. DINSTEIN, 1973. Texture features for image classification. *IEEE Transactions on Systems, Man. and Cibernetics. SMC-3 610-621.*

IDRISSA, M & M. ACHEROY, 2002. Texture classification using Gabor filters. *Pattern Recognition Letters 23: 1095-1102.*

JAIN, A.K. & F. FARROKHNIA, 1991. Unsupervised texture segmentation using Gabor filters. *Pattern Recognition.* 24: 1167-1186.

RANDEN, T., 1997. Filter and filter bank design for image texture recognition. *Ph.D. Thesis. Norwegian University of Science and Technology.*

RUIZ, L.A., A. FERNÁNDEZ & J. RECIO, 2004. Texture feature extraction for classification of remote sensing data using wavelet decomposition: a comparative study. *International Archives of Photogrammetry and Remote Sensing*. Vol.XXXV, ISSN 1682-1750. pp 1109-1114.

WELDON, T.P. & W.E. HIGGINS, 1998. An algorithm for designing multiple Gabor filters for segmenting multi-textured images. *IEEE Int. Conf. on Image Processing* 333-337.