TEXTURE FEATURE EXTRACTION FOR CLASSIFICATION OF REMOTE SENSING DATA USING WAVELET DECOMPOSITION: A COMPARATIVE STUDY

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ABSTRACT:

The extraction of texture features from high resolution remote sensing imagery provides a complementary source of data for those applications in which the spectral information is not sufficient for identification or classification of spectrally heterogeneous landscape units. However, there is a wide range of texture analysis techniques that are used with different criteria for feature extraction: statistical methods (grey level coocurrence matrix, semivariogram analysis); filter techniques (energy filters, Gabor filters); or the most recent techniques based on wavelet decomposition. The combination of parameters that optimize a method for a specific application should be decided when these techniques are used. These parameters include the neighbourhood size, the distance between pixels, the type of filter or mother wavelet used, the frequency or the standard deviation used to create the Gabor filters, etc. The combination of parameters and the texture method used is expected to be key in the success and efficiency of these techniques for a particular application.
In this study, we analyze several texture methods applied to the classification of remote sensing images with different types of landscapes, as well as the optimal combination of parameters for each group of data. For this purpose, we created a database with high resolution satellite and aerial images from two types of environments, representing two of the main applications of texture analysis in remote sensing: Urban and forestry. The texture classes defined in urban applications involve heterogeneity and symmetry, while in forest applications is important to know the type and density of vegetation. The results show that the type of application determines the technique and the combination of parameters to be used for optimizing accuracy. The combination of texture methods and spectral information improves the results of classification. Finally, some specific methods to correct the *border effect* should be developped before these techniques can be applied in practice.

1. INTRODUCTION

Multispectral information provided by airborne and satellite sensors is succesfully used for creating and updating cartography for forest and agriculture uses, as well as for monitoring urban sprawl. This information is valuable as a complement to the field data and the more traditional manual interpretation of aerial photographs, allowing for an increase in the efficiency of the processes by partially automatizing certain tasks, thus reducing costs of field data collection and improving the updating frequency due to the regularity of quality imagery data.
In forestry and urban studies, multispectral classification techniques provide suitable results when the classes defined represent structural and spectral homogeneous units, provided that the spectral response pattern of each class is sufficiently specific. This is the case of mountain areas where there are dense forests with uniform growth and a predominance of one or few species. However, mediterranean ecosystems present a wide structural and botanical diversity. A similar situation occurs in most of the peripheral urban areas, where there is a strong structural diversity and, consequently, an important spectral variability in the urban landscape units. This makes the process of classification using only spectral information more difficult, and some methods for the extraction of structural information from each type of unit are required.
Texture analysis offers interesting possibilities to characterize the structural heterogeneity of classes. The texture of an image is related to the spatial distribution of the intensity values in the image, and as such contains information regarding contrast, uniformity, rugosity, regularity, etc. A considerable number of quantitative texture features can be extracted from images using different methodologies in order to characterize these properties, and then can be used to classify pixels following analogous processes as with spectral classifications.
Many texture comparative studies can be found in the literature, usually carried out by employing standard image databases for the testing process. However, due to the lack of a widely accepted benchmark, all experimental results should be considered to be applicable only to the reported setup. Using images from the same database gives no guarantee of obtaining comparable experimental results (Ojala et al., 2002).
In this article we describe the application of several texture feature extraction approaches to classify different images from two main environments: forest and urban landscapes. The fundamental goals of this study were:

- To compare and evaluate four different approaches for the extraction of texture features applied to the classification of a variety of images in different environments, analyzing and assessing the different methodological parameters involved in the process.
- To study the potential of these techniques in order to classify (1) mediterranean forest landscape units with different density and types of vegetation, and (2) urban sprawl units.
- To assess the potential sinergy of the combination of texture and spectral data from high resolution satellite images, in order to classify complex landscapes.

2. TEXTURE ANALYSIS METHODS

In this chapter we will briefly describe the four methods used for texture analysis and feature extraction: (1) Statistical methods based on the grey level coocurrence matrix, (2) energy filters and edgeness factor, (3) Gabor filters, and (4) wavelet transform based methods.

2.1 Grey level coocurrence matrix (GLCM)

The elements of this matrix, *p(i,j)*, represent the relative frequency by which two pixels with grey levels "i" and "j", that are at a distance “d” in a given direction, are in the image or neighbourhood. It is a symmetrical matrix, and its elements are expressed by

$$p(i,j) = \frac{P(i,j)}{\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} P(i,j)} \tag{1}$$

where *Ng* represents the total number of grey levels. Using this matrix, Haralick (1973) proposed several statistical features representing texture properties, like *contrast*, *uniformity*, *mean*, *variance*, *inertia moments*, etc. Some of those features were calculated, selected and used in this study.

2.2 Energy filters and edgeness

The energy filters (Laws, 1985) were designed to enhance some textural properties of the images. This method is based on the application of convolutions to the original image, *I*, using different filters $g_1, g_2, ..., g_N$, therefore obtaining *N* new images $J_n = I * g_n$ $(n = 1,...,N)$. Then, the energy in the neighbourhood of each pixel is calculated. In order to reduce the error due to the *border effect* between different textures, a post-processing method proposed by Hsiao y Sawchuk (1989) was used. This method is based on the calculation, for each pixel of the filtered image J_n, of the mean and variance of the four square neighbourhoods in which each pixel is a corner, and assigning as the final value for that pixel the mean of the neighbourhood with the lowest variance, which is supposed to be more homogeneous and, consequently, should contain only one type of texture (no borders).

The edgeness factor is a feature that represents the density of edges present in a neighbourhood. Thus, the gradient of an image *I* is computed as a function of the distance “*d*” between neighbour pixels, using the expression:

$$\begin{aligned} g(i,j,d) = \sum_{(i,j)\in N} \{ & | I(i,j) - I(i+d,j) | + | I(i,j) - I(i-d,j) | + \\ & + | I(i,j) - I(i,j+d) | + | I(i,j) - I(i,j-d) | \} \end{aligned} \tag{2}$$

where *g(i,j,d)* represents the edgeness per unit area surrounding a generic pixel *(i,j)* (Sutton and Hall, 1972).

2.3 Gabor filters

These filters are based on multichannel filtering, which emulates some characteristics of the human visual system. The human visual system decomposes an image formed in the retina into several filtered images, each of them having variations in intensity within a limited range of frequencies and orientations (Jain and Farrokhnia, 1991). A Gabor filters bank is composed of a set of Gaussian filters that cover the frequency domain with different radial frequencies and orientations. In the spatial domain, a Gabor filter *h(x,y)* is a Gaussian function modulated by a sinusoidal function:

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

(3)

where σ_g determines the spatial coverage of the filter. In the frequency domain, the Gabor function is a Gaussian curve (Bodnarova et al., 2002). The Fourier transform of the Gabor function is:

$$H(u,v) = \exp[-2\pi^2\sigma_g^2((u - F\cos\theta)^2 + (v - Fsen\theta)^2)] \tag{4}$$

The parameters that define each of the filters are:

1. The radial frequency (*F*) where the filter is centered in the frequency domain.
2. The standard deviation (σ) of the Gaussian curve.
3. The orientation (θ).

For the purpose of simplicity, we assume that the Gaussian curve is symmetrical. The filter bank was created with 6 orientations (0º, 30º, 60º, 90º, 120º and 150º) and 3 combinations of frequency and standard deviation: *F*=0.3536 and σ =2.865, *F*=0.1768 and σ =5.73, *F*=0.0884 and σ =11.444. This operation produced a total of 18 filters covering the map of frequencies. Once the filters were applied and their magnitude computed, the image was convolved by a Gaussian filter (σ =5) to reduce the variance.

2.4 Wavelet transform

The use of wavelet transform was first proposed for texture analysis by Mallat (1989). This transform provides a robust methodology for texture analysis in different scales. The wavelet transform allows for the decomposition of a signal using a series of elemental functions called *wavelets* and *scaling*, which are created by scalings and translations of a base function, known as the *mother wavelet*:

$$s \in \Re^+ \quad u \in \Re$$

$$\psi_{s,u}(x) = \frac{1}{\sqrt{s}}\psi\left(\frac{x-u}{s}\right) \tag{5}$$

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:

$$Wf(s,u) = \int_{\Re} f(x)\frac{1}{\sqrt{s}}\psi^*\left(\frac{x-u}{s}\right)dx \tag{6}$$

In practice, wavelets are applied as high-pass filters, while scalings are equal to low-pass filters. As a result of this, 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.
Regarding previous work in image texture analysis using wavelet decomposition, different texture features have been extracted, sometimes from the fluctuations and in other cases from the details, depending on the authors. Sometimes, basic features directly extracted from the histogram were used, such as the local energy (Randen and Husoy, 1999) or variance filter (Ferro and Warner, 2002). Simard et al. (1999), however, used wavelet histogram signatures, while Van de Wouwer et al. (1999) compared the energy, wavelet histogram signatures and coocurrence features.

We compared the use of fluctuations and details, and four coocurrence features were calculated using them: *variance*, *inverse difference moment*, *contrast* and *correlation*.
In a comparative study about the evaluation of the performance of texture segmentation algorithms based on wavelets, Fatemi-Ghomi et al. (1996) stated that the identification of the most appropriate parameters to use in a method is as important a decision as the choice of which method to use. We also wanted to know, given our particular classification cases, the best group of methodological parameters to solve each particular problem. The following parameters were tested: the type of features, the window or neighbourhood size, the type of wavelet, the influence of the level of decomposition, and the use of the sum of the details or the fluctuations, or to consider them independently. All these items will be analysed in the tests and results section.

3. TESTS AND RESULTS

The different texture analysis methods and parameters were evaluated for application in two environments: mediterranean forested areas and growing urban areas. In this section, we will first describe the testing areas and the type of image data used, then we will analyze the selection of the texture parameters. Finally, we will compare the accuracy of the classification obtained with the specific methods used, as well as the spectral versus texture classification for one of the forest testing areas, where Quickbird images were available.

3.1 Data and test areas

Imagery from a total of four areas was used for evaluation, three forested and one urban, all in the mediterranean region of Spain.

1. Forest 1: Located at the *Sierra de Espadán, Castellón*, near the central mediterranean coast of Spain, with dominance of forest (*Pinus halepensis* and *Quercus suber*) and shrubs (*Quercus coccifera, Ulex,...*), olive tree crops and rocky areas. Seven classes were defined: *high-density forest, mid-density forest*, areas combining *forest-shrub, shrubs, scattered trees, scattered shrubs*, and *olive trees.* For the purposes of evaluation, a mosaic image was created from aerial orthophotos scanned to 1m of spatial resolution.
2. Forest 2: This area is located slightly south and west of the previous one, in *Ayora, Valencia*, farther from the coast and having a type of climate meso-mediterranean. The vegetation of this area is mainly composed of forest (*Pinus halepensis*) and mediterranean shrub, usually mixed, and mountain crops (*Amigdalus communis, Olea europaea, Ceratonia siliqua*) sometimes forming flat terraces on the sides of the mountains. The trees of this area are more scattered, in part because of a high recurrence of wildfires over the last several years. Nine classes were defined: *high-density, mid-density* and *low-density forest, high-density* and *low density shrub, cereals, almond trees, reforestation* areas, and crops on *terraces*. The data were digital orthophotos with 1m of spatial resolution, that were also mosaicked to form an image with a variety of zones (figure 1).

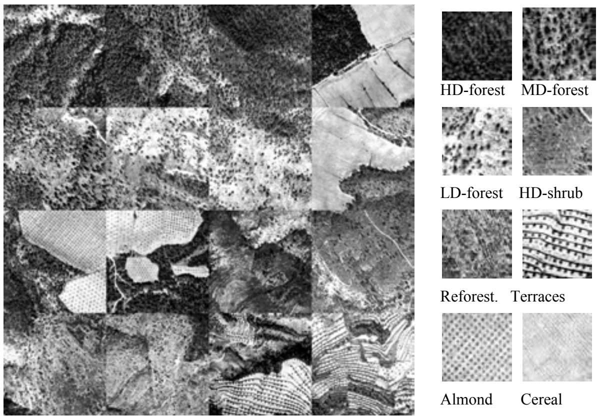

Figure 1. Orthoimages mosaic of forest area 2, *Ayora* (left), and detail examples of eight of the classes defined (right).

3. Forest 3: Located in the south of *Menorca*, one of the Balearic islands in the western Mediterranean sea. The landscape is composed of small forested areas (*Pinus halepensis, Quercus ilex*), and shrubs (*Quercus coccifera, Ulex, Pistacia lentiscus, Rhamnus alaternus*), usually combined with scattered trees (*Olea europaea var. sylvestris*), pasture areas, crops and residential areas. Seven forest and agricultural classes were defined: *dense forest, forest-shrub, dense shrub, scattered trees*, herbaceous vegetation or *weeds*, *cereal or pasture*, and *fallow*; as well as two non-vegetation classes: *residential* areas and *sea*. In this case, a high-resolution panchromatic satellite image (QuickBird) was used, but resampled to 2.4 m to keep visual coherence of the texture classes analysed, and to be able to compare them with the multispectral image from the same satellite.
4. Urban: Located in the northern area of the city of *Valencia*, which has experienced an important urban sprawl during the last several decades, and the surrounding towns. The classes considered were: *old urban* areas, *new urban* areas, more dispersed *residential* areas located outside of the city, *industrial* areas and barren soil, *horticulture,* and *citrus* fruit *orchards*. A panchromatic image captured by the satellite QuickBird was used, in this case resampled to 5 m.

3.2 Selection of methodological parameters

As we stated above, there are several methodological parameters that should be optimized for each type of application (forest or urban). We will now describe the results obtained in the parameter selection process, method by method. One of the most relevant parameters is the neighbourhood size, which is obviously related to the spatial resolution of the images. Therefore, a specific analysis is required for each of the images with a different resolution.

- Coocurrence matrix method: The distance between pixels (from 1 to 3) does not seem to effect on the results, so a distance of one pixel was used. In general, the increase of the window size rises the level of the accuracy in the inner part of the texture areas, but produces a progressive increase in error due to the *border effect.* A neighbourhood size of 25x25 was used, except for the forest area 3 (*Menorca*), where a size of 15x15 optimized the accuracy results.
- Energy filters and edgeness: A common window size of 7 pixels was used to apply the filters, while for the post-processing operation the window size ranged from 7 to 15 pixels, depending on the area. The optimal distance for the edgeness factor was 3 pixels.
- Gabor filters: The main parameters are the standard deviation of the filter, what has an interpretation similar to the window size, and the frequency. After the selection process, banks of filters with standard deviations of 2.86, 5.73 and 11.44, and respective frequencies of 0.3536, 0.1768 and 0.0884 were created. They were defined by the six dominant directions and then averaged to eliminate the orientation factor.
- Wavelet based method: Four types of wavelet families were tested, *Daubechies* 4 and 8, and *Coiflet* 12 and 24, as well as 3 different levels of *fluctuations* and *details*. The best results were obtained using the wavelet Coiflet-24 and its reconstructed details form the 3 levels, because each level provides texture information from a different scale (figure 2).

As a result of these preliminary tests, a reduction of the texture features to be used in the comparative classification process was made for each of the four methods tried.

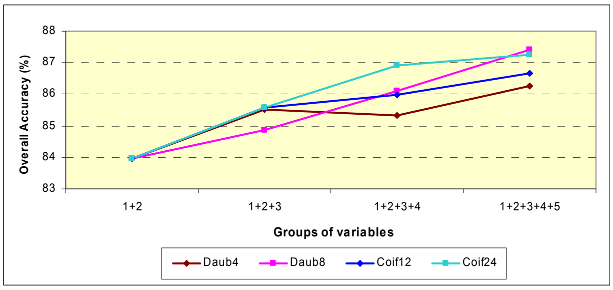

Figure 2. Results for the selection of wavelet type and level of decomposition used for the urban area. (Groups of variables: 1:Original image. 2:Textural variables from original image. 3:Variables from details of 1st level. 4:Variables from details of 2nd level. 5:Variables from details of 3rd level).

3.3 Comparison of methods

The algorithm used in the classification process was the maximum likelihhod classifier, and two sets of texture samples were defined for each area: a training set and a testing set, both independent and chosen to be representative of the different classes considered. After the aforementioned selection of variables, several combinations of groups of variables were tested to compare the texture methods. The results of the different classifications, in terms of overall accuracy, are shown in figure 3.

As expected, due to the spectral heterogeneity of most of the classes, the lower accuracy levels correspond to the only spectral classification that uses the four multispectral bands of the QuickBird image (only for the area of Menorca). The accuracy increases by combining different groups of texture variables.

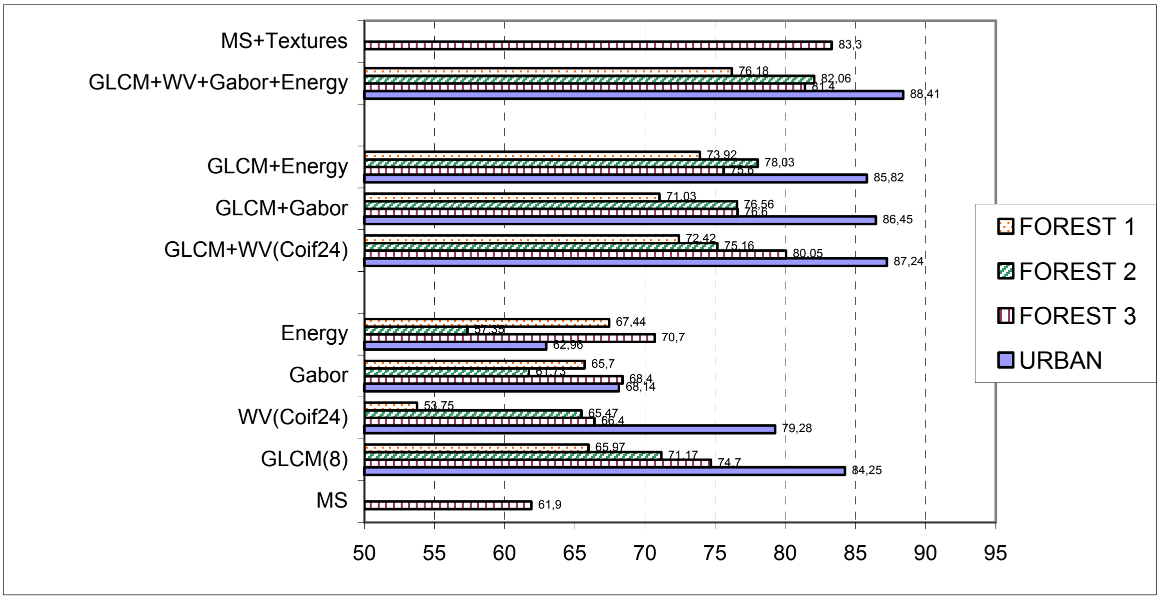

Figure 3. Overall accuracy percentages obtained for the four test areas using different methods and combinations of texture variables.

Considering the different texture methods independently, it cannot be stated that there is a universal method that is best for all cases, since the results seem to depend on the type of problem treated. However, they are usually better when statistical coocurrence features are used. The combination of these statistical variables with any of the other methods, energy filters, Gabor filters or wavelets, produce a significant increase in the overall accuracy levels, especially with the latter. This is problably due to the complementary condition of the methods based on filtering with respect to the direct statistical method based on the GLCM. It is interesting to note that using only three Gabor filters (three features) it is possible to obtain relatively good classification results.

In the forest areas, the texture classification provides accurate results in those classes where there are mixed spectral responses, such as reforestation, and where the density of vegetation is a crucial factor, such as high, mid and low-density forest. Some examples are shown in figure 4.

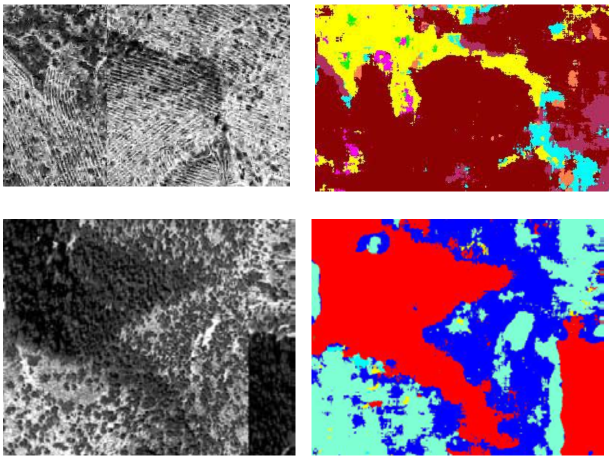

Figure 4. Detail images of texture classification of mixed areas with *reforested* and *mid-density* forest (above); and three different levels of forest density (below).

Regarding the urban application, there are some classes that are accurately classified using texture methods, such as residential areas and old urban areas, but there are many commission errors (34%) in the industrial class. It is difficult to create a representative texture signature of this area, probably because the spatial resolution used is not aproppiate for this class. Table 1 shows the specific accuracy levels for the different urban classes, and figure 5 a detail of the classified image.

Class	Producer's accuracy	User's accuracy
Citrus orchards	80.07	86.18
New Urban	88.09	92.23
Horticulture	86.38	87.66
Old Urban	89.04	94.70
Residential	96.70	98.83
Industrial	94.10	65.99

Table 1. Accuracy percentages of the classification of the urban area using all the texture features (4 methods) combined.

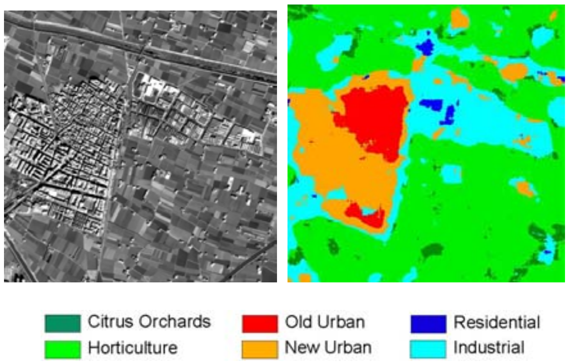

Figure 5. Texture classification of a detail image of the urban area.

3.4 Spectral vs. texture classification

The classification of forest area 3 (Menorca) was done in two steps. In the first step, the non-vegetation classes (*residential* and *sea*) were masked out by taking advantage of the spectral and radiometric properties of the QuickBird multispectral image. The sea was masked by directly thresholding the infrared band, and the residential areas (also including roads and cliffs) were extracted by thresholding the third principal component of the four bands. This is easily achieved using these images, due to their high radiometric resolution (11 bits). Once the two masks had been applied over the panchromatic image, the second step consisted of the vegetation classification of the remaining areas. In addition, this comparative process of classification was carried out using both texture and spectral bands. Table 2 shows the comparative results in terms of producer's and user's accuracies.

	MULTISPECTRAL		**TEXTURES**		**MS+TEXTURES**	
CLASS	**Producer's Accuracy**	**User's Accuracy**	**Producer's Accuracy**	**User's Accuracy**	**Producer's Accuracy**	**User's Accuracy**
Dense forest	54.11	57.02	58.00	78.38	53.67	82.92
Shrubs	62.26	55.39	88.46	94.76	88.90	94.21
Pasture-cereal	99.78	99.74	92.07	92.11	96.76	96.21
Scattered trees	41.96	42.25	85.27	75.22	87.00	75.67
Forest-shrub	21.45	25.56	73.71	54.79	76.10	52.47
Weeds	61.80	58.56	90.36	89.70	94.78	95.65
Fallow	98.69	97.42	87.34	91.02	97.13	100

Table 2. Results of the classification of Menorca using spectral variables, texture variables and a combination of both.

Comparing the spectral and texture classifications in table 2, we see that spectral classification is better suited for those landscape units with a specific spectral response pattern and well differenciated from the rest of the units, such as *pasture* land and *cereal* crops, or *fallow*. The distribution of grey levels in these two classes is very homogeneous, so they are more difficult to discriminate by texture methods. On the other hand, texture techniques are very efficient in classifying lanscape units that contain a high spectral heterogeneity, such as scattered trees, forest-shrub and dense shrub. These classes are not very accurate when classified using only spectral band. Another interesting aspect is the the integration of spectral and texture bands for classification has a synergic effect on the results, in some cases even improving the accuracy of both groups of classes.
However, it is important to note that the reported results refer to the inner areas of the texture units and not to the borders between textures. In these areas, the *border effect* decreases the overall accuracy to 47%. An example of this effect is shown on the detail image of figure 6. Some previous tests have shown how the post-processing operation, described for the energy filters, increases the accuracy in the border areas in a 27% (Ruiz et al., 2001)

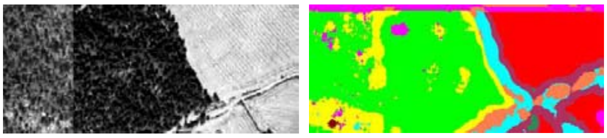

Figure 6. Example of the *border effect* in texture classification.

4. CONCLUSIONS

This study has been focused on two main applications of texture analysis in remote sensing: the classification of forest landscape units and urban areas. The former holds a special interest for mapping forest areas, the latter is a first step in monitoring urban sprawl. Some important aspects can be concluded:

- The texture methods provide an alternative to the spectral methods for the classification of forest units with a high spectral heterogeneity, or when the classes are defined by differences in vegetation density.
- In urban classification, the texture methods are useful for discriminating old urban areas and new residential spots, but they introduce important errors in the classification of industrial areas, so spectral information should be used in addition to texture.
- A universal criteria in order to use the idoneous texture extraction method for classification does not seem to exist. Therefore, the selection should be in funtion of the type of landscape units defined in each application.
- Furthermore, the combination of different texture methods improves the classification results, especially when combining statistical methods based on the GLCM with the details of different levels obtained from the wavelet transform. The Gabor filters allow an important part of the texture information to be condensed into a few variables.
- Before beginning the texture classification process, it is important to previously select the methodological parameters and features to reduce the volume of data and to optimize the discrimination power of these techniques.
- The main limitation for the standard application of texture methods in image classification is probably the *border effect*, inherent to texture analysis and which introduces important errors in the transition areas between texture units. Further work should be done to reduce this effect.

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