Evaluation of texture analysis techniques to characterize vegetation

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ABSTRACT

The extraction of numeric features to characterize textures on images takes special relevance in certain satellite and aerial images classification processes. The wide range of the methodological approaches used and their applications in the earth observation (i.e., vegetation analysis, urban distribution and growing, landscape analysis, etc.) makes difficult the appropriate selection of the method in each particular case. In this work, several texture analysis techniques were evaluated: statistical features extracted from the *grey level co-ocurrence matrix*, methods based on *energy filters* and the *edgeness* factor, and the most recent based on the *wavelets* decomposition theory. In addition, different methodological parameters were tested, the most relevant being the neighbourhood size chosen for the determination of the texture features, as well as the distance between pixels and the number of grey levels used.
The wavelets based methods offer a wide range of options, specially regarding the type of mother wavelets used, or if the feature extraction is made from images that result from the standard decomposition or from the decomposition and further reconstruction using the inverse transform. Several types of mother wavelets and both decomposition options were tested. One of the best advantages of this methods is that multiresolution analysis allows the combination of features from different levels of resolution.
The evaluation was carried out using a mosaic of real images, with the goal of discriminating between different types of crops. The results show that the combination of the original and wavelet features together yields a better performance when the appropriate wavelet is chosen. The wavelets with highger support, such as the Coif-24, generated better results, and most of the texture information of the tested vegetation classes is contained in the lower levels of decomposition.

1. INTRODUCTION

Texture analysis methods have been used with positive results in many remote sensing applications, such as mapping and analysis of urban expansion, classification of forests, characterization of vegetation to study regeneration processes, or landscape analysis. The texture of an image is related to the distribution of grey levels in the image, so we can consider microtextures, when a small neighbourhood is analysed for the distribution of values, or macrotextures, when the analysed area is larger.

The features used to describe the texture can be obtained by several methods. The most traditional are the statistical approaches, which are based on the measurement of the occurrences of each grey level value in a particular neighbourhood, known as first-order statistics, or on the coocurrences of the different grey levels between two pixels of the neighbourhood, as described by Haralick et al. (1973), and called second-order statistics. Other approaches are based upon filtering the image and then computing the energy for each pixel or for each pixel neighbourhood (Laws), or by computing the edgeness of a region by applying gradient filters. Autocorrelation measures, Fourier transform based features (), Gabor filters banks (Turner, 1986), Gauss-Markov random fields (Kashyap et al., 1982), or fractals models (Pentland, 1984), among others, are also techniques that have been used to characterize textures in different applications.

Most recently, the development of the theory of wavelets has supposed the beginning of the application of this technique in order to improve the results of texture classification processes. The use of a pyramid-structured wavelet transform for texture analysis was first suggested by Mallat (1989). Since the texture of an image is a function of the scale, an advantage of wavelet decomposition is that provides a unified framework for multiscale texture analysis. Due to the wide range of possibilities and variations that wavelet decomposition offers, these studies have been usually focused on specific methodologies. Thus, for instance, Chang and

Kuo (1993) used wavelet packets, and Unser (1995) a variation of the discrete and overcomplete wavelet decomposition. In addition, some comparative studies have been done, testing different combinations of internal parameters of texture analysis methods based on the wavelet transform (Fatemi-Ghomi et al., 1996), or comparing more traditional filtering approaches with some variations of wavelet based methods (Randen and Husoy, 1999). In all cases, the testing data sets used were composed of standard images, usually obtained from the Brodatz database (Brodatz, 1966), which is valid for comparison purposes, but particular real problems often render unequal performances, so they need to be specifically tested. In fact, the results obtained do not lead to an optimum methodology or a unique combination of parameters to be used.

The wavelet transform decomposes the original image into a low-resolution image and several detail images. The low-resolution images are obtained by iteratively low-pass filtering the original image, and the detail images contain the information lost in the process. In general, the *energy* and *varianc*e of the detail images are the most common features extracted for texture classification. However, Van de Vower et al (1999) used, as texture features, histogram and coocurrence signatures computed from the same detail images. They noticed that the results obtained with the first-order set (histogram) and with the second-order set (coocurrence) of features were different depending on the specific class considered. This result reinforces the former statement that the method, texture features and parameters used should be specifically chosen for each application or group of applications.

The texture of an image becomes an important propertie for the classification of vegetation units. On one side, it provides spatial information about the density and distribution of spontaneous vegetation, useful in forestry applications such as classification of landscape units in forested environments (Marceau et al., 1994), or determination of forest canopy densities for regeneration studies (Ruiz and Fdez.-Sarría, 2000). In addition, it provides information about the spatial arrangement of plants and trees in orchards for agricultural applications like crop classification, using high spatial resolution images as initial data for the extraction of texture features.

In this paper, we evaluate three main groups of texture analysis methods (statistical, filtering and wavelet based) to discriminate agricultural landscapes using high resolution images from central Spain. The experiments are focused on testing the variations of several parameters related with texture analysis from wavelet decomposition, like the window size, the type of mother wavelet used, the influence of the decomposition level, the convenience to work with the decomposed detail images or with the reconstructed ones, or the selection of the most discriminant features. The classification results obtained from the different variations of the wavelet parameters are compared to the results obtained from the best statistical and filtering features.

The classification of images by textures is always limited by the *edge effect*, or the high missclassification rate produced in the transition areas between classes, due to the fact that the classification of each pixel is determined by the values of its neighbourhood, so the pixels from the border areas will be affected by the pixels values of the adjacent classes. The effect will increase when larger window sizes are used to compute the texture features. In this sense, all of the classification results should be referred to the internal and external areas of the texture classes (Ruiz et al., 2001, Ferro and Warner, 2002).

2. METHODS

In this section we will describe the experimental procedure followed for the evaluation of different texture methods for the characterization of vegetation. First, we will explain the image data used and the texture classes defined. In the next three sections, we will describe the feature extraction methods used: grey levels coocurrence matrix features, filtering, and wavelet decomposition analysis. Finally, a description and discussion of the experimental tests is made attending to the different parameters considered, as well as the classification process used to obtain the final results.

2.1. Experimental data

The image data used for the study were extracted from a series of aerial photographs from a large region of central Spain, dominated by a diverse agricultural landscape including extensive and intensive crops, sometimes combined with disperse oak trees forming *dehesas*. Some urban areas were included to increase the diversity in the classification problem.

The initial aerial photographs, with an approximate scale of 1:30.000, were digitised to obtain 2 m. spatial resolution images. Then, several areas were extracted to form a mosaic image with the criterium of preserving a high variety of significant texture classes and reducing the amount of data to decrease the computing time on the tests. The final mosaic was composed of six subimages as shown in figure 1.

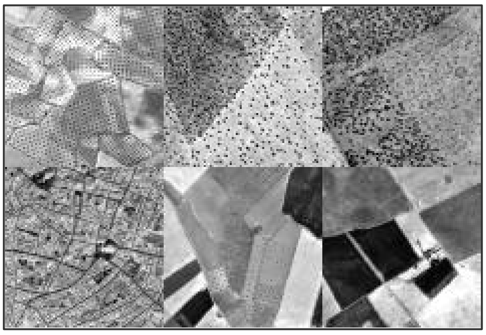

Figure 1. Mosaic image used for the texture analysis tests.

A total of 12 texture classes were defined, 6 of them may be considered as fine textures: *Vineyards* (V); *Non-Harvested Cereal* (CN); *Harvested C*ereal (CC); *Alfalfa* (A); *Harvested Alfalfa* (AC); and *Maize* (M). The other 6 correspond to coarse textures: *Vineyards combined with Olive trees* (VO); *Olive trees* (O); *Dehesa combined with Cereal* (DC); *High density Dehesa* (DA); *Low density Dehesa* (DB); and *Urban areas* (U) (figure 2).

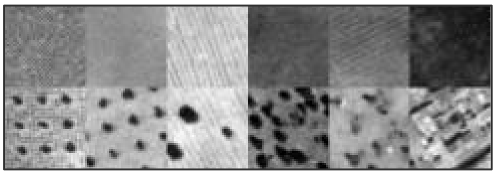

Figure 2. Image samples of the 12 texture classes. Fine textures in upper row (from left to right): V, CN, CC, A, AC and M. Coarse textures in lower row (from left to right): VO, O, DC, DA, DB and U.

The extraction of texture features from the mosaic image was accomplished using three different methods: features derived from the grey level coocurrence matrix, energy filters, and wavelet decomposition based features.

2.2. Coocurrence features

These features are based on the computation of the grey level coocurrence matrix (GLCM) in the neighbourhood of each pixel. A generic element of this matrix, *p(i,j)*, represents the relative frequency in which two grey levels, *i* and *j*, ocurr in that neighbourhood between two pixels separated a distance *d* in a given direction *q*:

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

where N_g is the number of grey levels. The neighbourhood is defined by the window size, which is an important parameter to be considered. Since the defined texture classes do not follow any particular orientation, the results of four directions were averaged for this test. After the results obtained in former experiments (Ruiz, 1998 and 2000), the distance between pixels (*d*) used was always 1 pixel.

A total of 8 texture features were initially computed from the GLCM (Haralick et al., 1973):

Uniformity: $$\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} p(i,j)^2$$

measures the homogeneity, with high values when the spatial distribution of the grey levels is almost constant.

Entropy: $$-\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} p(i,j)\cdot \log\left[p(i,j)\right]$$

is a measure of the randomness of the intensity distribution.

Contrast: $$\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} (i-j)^2 \cdot p(i,j)$$

is related to the spatial frequency of the neighbourhood. High values of contrast are indicative of high grey level values off the principal diagonal of the matrix.

Mean: $$m = \sum_{i=0}^{N_g-1} i \cdot p_x(i)$$

where $$p_x(i) = \sum_{j=0}^{N_g-1} p(i,j)$$

provides information about the overall intensity level in the neighbourhood.

Variance: $$\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} (i-m)^2 \cdot p(i,j)$$

is a measure of heterogeneity, with higher values when the grey levels differ from the mean.

$$\textit{Inverse difference moment :} \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}\frac{p(i,j)}{1+(i-j)^2}$$

is inversely related to the *contrast*.

$$\textit{Product moment :} \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}(i-m)\cdot(j-m)\cdot p(i,j)$$

is a measure of local homogeneity. Finally, if the *product moment* is normalized (divided) with respect to the variance, the *correlation* is obtained, which represents the eigth coocurrence feature computed.

2.3. Filters

The filtering approaches are based on the application of convolutions to the original image and then computing some basic indices, such as energy, over the neighbourhood of each pixel.

The textural energy features are based on the convolution of the initial image I with a variety of kernels g_1, g_2,...,g_N, yielding N new images $J_n = I * g_n$ $(n = 1,...,N)$. Each filter is designed to enhance a different texture property on the image. Two sizes of filters were used, 5x5 and 7x7, considering that they were the most appropriate for the type of elements present in our texture classes.

We used 6 filters (figure 3) proposed by Laws (1985): *Level (L)*, that gives information of the average grey level in the neighbourhood; *Gradient (E)* is and edge enhancing filter; *Shape (S)* enhances certain shapes on the grey level dimension; *Wave (W)*; *Ripple (R)*, and *Oscillation (O)*, that enhance different waving shapes on the image. In addition, the *Laplacian of a Gaussian* filter *(LoG)* was also computed.

	7 x 7									5 x 5					
L =	[	1	6	15	20	15	6	1	]	[	1	4	6	4	1]
E =	[	-1	-4	-5	0	5	4	1	]	[	-1	-2	0	2	1]
S =	[	-1	-2	1	4	1	-2	-1	]	[	-1	0	2	0	-1]
W =	[	-1	0	3	0	-3	0	1	]	[	-1	2	0	-2	1]
R =	[	1	-2	-1	4	-1	-2	1	]	[	1	-4	6	-4	1]
O =	[	-1	6	-15	20	-15	6	-1	]	[					]

Figure 3. 1D representation of the 7x7 and 5x5 filters used on the tests (Laws, 1985).

A problem that arises with this approach is the introduction of significant errors along the boundaries between different textures in the image, formerly called the *edge effect*. It might be the case of obtaining energy values, in the areas located on the boundaries, that are closer to a third texture than to the ones included in the 7 x 7 window, with the subsequent error in classification. To reduce this effect, a new level of processing was applied , as proposed by Hsiao and Sawchuk (1989): for each pixel on the textural energy image J_n, the mean and variance of the four neighbourhoods for which the pixel is the corner are computed, and the new pixel takes the value of the mean of the quadrant that has the smallest variance (figure 4).

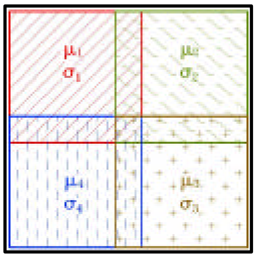

Figure 4. Diagram that represents the further processing level on the energy features to reduce the *edge effect*.

Another texture feature computed that can be included into the filtering methods is the *edgeness,* based on the idea of Sutton and Hall (1972), in which texture is conceived in terms of edgeness per unit area and represented by the gradient (the sum of the absolute value of the differences between neighbouring pixels) as a function of the distance between the pixels. For a given distance d (tested as a variable texture parameter) and subimage $I,$ defined over a neighbourhood N, the *edgeness* is computed with the following expression:

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

where $g(i,j,d)$ represents the edgeness per unit area for a generic pixel (i,j) in the image, and d is a variable parameter to be studied for each particular group of textures.

2.4. Wavelet based texture analysis

A wavelet is a scaled and translated version of an elemental function called a *mother wavelet*

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

where s is the scale parameter and u the translation parameter. The wavelet decomposition of a function can be computed by applying each of these wavelets to the function itself

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

In practice, 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 (Walker, 1999). The original image is thus decomposed into a set of subimages at several scales, some of them contain the *averages* of the original image at a particular scale, and the other subimages represent the *details*. Since most relevant texture information is removed by iteratively low-pass filtering, the *average images* are not usually considered to obtain texture features (Van de Wouver, 1999).

The technique used for the application of a discrete wavelet transform consists of the convolution of the digital image with a smoothing filter (*scaling*) and a band-pass filter (*wavelets*) along two orthogonal directions. The combination of these two filters along the vertical and horizontal directions renders four new output images for each level of decomposition, denoted by a, h, v, and d. The first one represents the *average* and the rest represent the first-order horizontal, vertical and diagonal *details*, respectively. It is important to mention that the wavelet decomposition entails the downsampling of the image by a factor of two, so each level of decomposition represents a lower scale or spatial resolution than the original image.

The application of the inverse transform of each output *detail* image produces a reconstructed version of the horizontal, vertical and diagonal *details*, denoted by H, V, and D, that contain high frequency information on different scales depending on the level of decomposition of the *detail* images. The reconstruction process, named *multiresolution analysis*, entails the upsampling of the images to the original size (figure 5). Considering that at each level of decomposition we are representing a down-scaled version of the image, the original image may be understood as a 0-level image, containing information at the original scale. This is an important aspect because the texture is a scale-dependent property, and each particular texture class usually has an optimum scale or resolution level for representation and feature extraction.

Once the decomposed and reconstructed images of the details were obtained, several texture features were computed for every output image. The features were selected among the statistical and filter based texture variables proposed on sections 2.2 and 2.3, on the basis of a separability criterium.

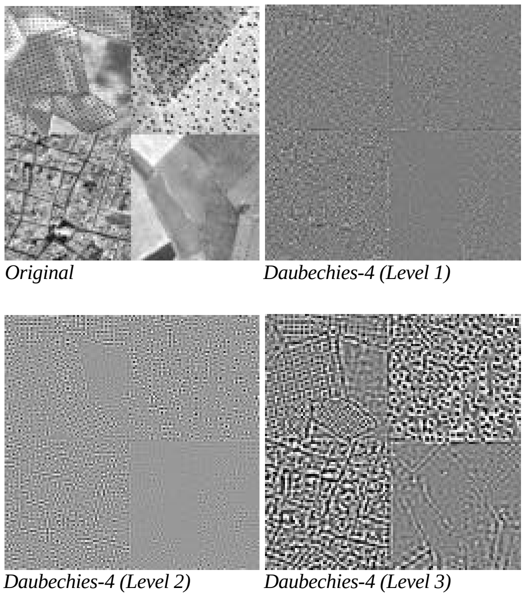

Figure 5. Detail of the original image before and after the respective three levels of wavelet decomposition and further reconstruction using only the *detail* components (V, H and D). The mother wavelet used is the Daubechies-4.

2.5. Experimental procedure

An important issue in texture analysis, especially when the wavelet decomposition method is used, is the selection of the most appropriate set of methodological parameters for each specific problem of texture classification. In this study, different variations of the following parameters were tested:

- *Window size*, or the neighbourhood to be considered to compute the values of the texture features for each pixel.
- The *texture features* that provide a better discrimination between classes. The selection was made between 8 statistical and 7 filtering features, as described above.

- *Type* of mother *wavelet* used. Six different wavelets were tested: Haar, Daubechies 4 and 8, Coiflets 6, 12 and 24.

- Influence of the *wavelet decomposition level*. Three levels were tested.

- Whether to use the *decomposed or* the *reconstructed detail* images to compute the texture features.

- Whether to use the *independent detail* images *or* the *sum of details* (H+V+D) for each level of decomposition.

Aditional parameters, such as the *distance* between pixels (*d*) to compute the coocurrence matrix or the *edgeness*, and the *number of grey levels* used, were studied in previous works for similar classification problems (Ruiz, 1998).

A pre-selection of two parameters, the influence of the *decomposition level* and the use of *independent details or the sum of the details*, was made by means of a statistical separability analysis using the Jeffries-Matusita distance. The rest of the parameters were directly evaluated by means of the classification process.

The classification method used to assign a texture class to each pixel on the image was based on the Bayesian maximum likelihood rule. Three different sampling sets were defined: the first was used as the learning set to obtain the decision functions, the other two were testing sets, one to evaluate the errors on the internal areas of the different textures, and the last set was used to evaluate the errors within the boundaries between classes, which are particularly high in texture classifications, due to the *edge effect*.

3. RESULTS AND DISCUSSION

Attending to the classification results, the first conclusion that should be pointed is that the classes with finer texture (cereal, alfalfa, maize,...) have a lower producer's classification accuracy on the external areas (boundaries between classes) than the classes with coarser textures (olive trees, dehesas, urban,...). Therefore, the default error in assigning classes to those pixels that are located on the borders of the texture areas is higher for finer textures, probably because the combination of two or more fine textures is more likely to be confused with heterogeneous or coarse textures, due to the higher dispersion of the texture signatures that the coarse textures naturally present.

From the 15 different texture features computed, the best classification results were obtained using 6 of them: variance, contrast, inverse difference moment, correlation, edgeness and energy. A window size of 21 x 21 pixels was selected taking into account to preliminary results and the type of classes, considering a trade-off between the classification accuracies of the internal and external areas. In general, the increase of the window size provides better results in internal areas and worse in external areas of the texture regions.

The separability tests showed that the generation of texture features for each of the independent *detail* images in the wavelet decomposition process does not increase the overall separability distance between classes, but multiplies by 3 the number of variables to compute. Therefore, the final classification results were obtained by using the sum of the horizontal, vertical and diagonal *detail* images.

In order to determine the influence of the wavelet decomposition level, the 6 most relevant features were computed for all the images derived from decomposition levels 1, 2 and 3, and for level 0 (original image without decomposition). A series of separability analysis were carried out to find the best 6 variables from a set of features from the 4 levels. The average results are shown on table 1, ordered by the percentage of time that a variable from a particular level was selected. About half of the times, the best variables were from level 0 (without wavelet decomposition), and the relevance of the variables was progressively lower as the level increased. In addition, the overall accuracies of four classifications using the wavelet Daubechies-4, with features of levels 0, 1, 2 and 3 were 86.1%, 74.7%, 57.0% and 46.2%, respectively. Therefore, in this case most of the texture information is included in the higher resolution levels.

Table 1. Influence of the decomposition level of the wavelet transform, expressed as the percentage of variables from different levels included among the best discriminant features.

Decomp. Level	0	1	2	3
% of var. included	48%	24%	18%	10%

Regarding the use of the decomposed or the reconstructed *detail* images to compute the texture features, two classifications were compared using the wavelet Daubechies-4. The overall accuracy was 65.7% when the decomposed images of the 3 levels were used, and 77.8% using the reconstructed ones.

Finally, figures 6 and 7 show the overall accuracies of a series of classifications to compare the influence of the type of wavelet and the convenience to use features computed from the original image (level 0), from the wavelet transforms with three level of decomposition (levels 1+2+3), or from the combination of all of them (levels 0+1+2+3).

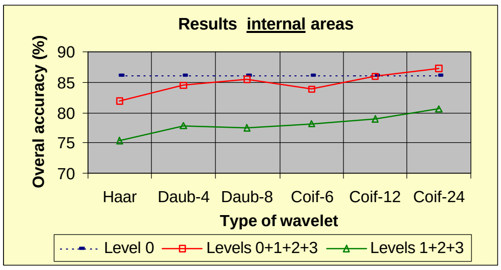

Figure 6. Classification results for **internal** areas using different types of wavelets and 3 different sets of features (level 0 means original image).

Figure 6 shows the results for the internal areas, without consideration for the *edge effect*. In those areas, the use of the original image always yields better results (86.1%) than the wavelet transform images. However, the combination of the original (level 0) and the wavelet features together produces a better performance when the appropriate wavelet is chosen. Thus, while the Haar wavelet has a relatively poor performance, the Coiflets work better, especially when the support is increased. The wavelet Coif-24 combined with the original image provide the best results of the tests (87.2%).

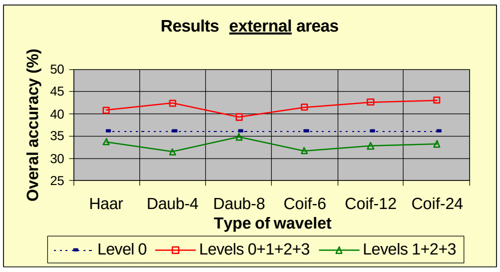

Figure 7. Classification results for **external** areas (*edge effect*) using different types of wavelets and 3 different sets of features (level 0 means original image).

The same tendency is observed in the external areas (figure 7), those in which the edge effect makes the accuracy of the classification decrease sharply. The combination of the features from the original image with the wavelet features provides better results with all the types of wavelets tested, but specially with the Coif-24, where the classification accuracy for those areas is increased by 6.4% with respect to that obtained only from the original image.

Figure 8 shows an example of the classified image used in the tests, where 12 texture classes were defined.

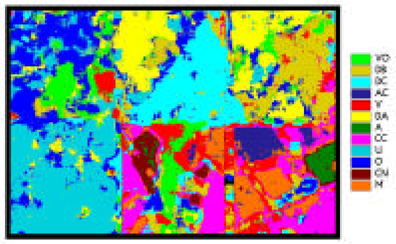

Figure 8. Classification of the mosaic image on figure 1 in 12 agricultural classes using texture features.

CONCLUSIONS

Texture classification of agricultural landscape images is a useful method to identify crops using traditional statistical features, though the edge effect inherent to these methods usually produces poor results on the boundaries between classes.

The combination of these features with those obtained from wavelet decomposition of images on several levels may increase the accuracy of the classification when the mother wavelet used in the transformation is properly chosen. Most of the texture information is contained in the lower levels of decomposition, and the reconstructed images (H, V and D) applying the inverse wavelet transform seem to provide better results than the decomposed images (h, v, and d).

In general, the wavelet approach provides a better performance for those areas that are on the boundaries between different textures. Therefore, the methods based on wavelets seem to reduce the *edge effect* of the classification.

The type of wavelet used is an important parameter. In our tests, the wavelets with higher support, such as the Coif-24, generated better results. However, further experiments should be done, using a wide variety of wavelets, in order to select the most appropriate type for each application.

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