



# Textural approaches for vineyard detection and characterization using very high spatial resolution remote sensing data

Carole Delenne, Sylvie Durrieu, Gilles Rabatel, Michel Deshayes,  
Jean-Stéphane Bailly, Camille Lelong, Pierre Couteron

## ► To cite this version:

Carole Delenne, Sylvie Durrieu, Gilles Rabatel, Michel Deshayes, Jean-Stéphane Bailly, et al.. Textural approaches for vineyard detection and characterization using very high spatial resolution remote sensing data. International Journal of Remote Sensing, 2008, 29 (4), pp.1153-1167. 10.1080/01431160701311259 . hal-01196900

**HAL Id: hal-01196900**

**<https://hal.science/hal-01196900>**

Submitted on 15 May 2020

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

## Textural approaches for vineyard detection and characterization using very high spatial resolution remote-sensing data

C. DELENNE\*†, S. DURRIEU†, G. RABATEL‡, M. DESHAYES†, J.S. BAILLY†, C. LELONG†, P. COUTERON§

† UMR TETIS, CEMAGREF - CIRAD - ENGREF, 34093 Montpellier, France

‡ UMR ITAP CEMAGREF - ENSA - CIRAD, 34196 Montpellier, France

§ French Institute of Pondicherry, PB 33, 605001 Pondicherry, India

(Received 00 Month 200x; In final form 00 Month 200x)

Vine-plot mapping and monitoring are crucial issues in land management, particularly for areas where vineyards are dominant like in some French regions. In this context, the availability of an automatic tool for vineyard detection and characterization would be very useful. The objective of the study is to compare two different approaches to meet this need. The first one uses directional variations of the contrast feature computed from Haralick's cooccurrence matrices and the second one is based on a local Fourier Transform. For each pixel, a 'vine index' is computed on a sliding window. To foster large-scale applications, test and validation were carried out on standard very high spatial resolution remote-sensing data. 70.8% and 86% of the 271 plots of the study area were correctly classified using the cooccurrence and the frequency method respectively. Moreover, the latter enabled an accurate determination (less than 3% error) of interrow width and row orientation.

**Keywords:** Texture; Image analysis; Cooccurrence; Fourier Transform; Vineyard

### 1 Introduction

Thanks to the increased availability of remote sensing data and of more powerful computers, automatic analysis methods can be developed to build or update geographical databases for land management. Accurate digital mapping of vineyards for wine-growing regions such as Languedoc-Roussillon (France) could be extremely useful for many reasons. For example, these maps can be integrated within Geographical Information Systems (GIS) which can be used by winegrower cooperatives to improve the monitoring of quality compliance in areas registered in the list of Controlled Origin Denomination. The management of pollution, erosion and flood risks is another field that can take advantage of these maps. Indeed, these risks, depending on culture and soil surface condition, are worsened by mechanization and intensive cropping practices (Wassenaar *et al.*, 2005; Vincini *et al.*, 2004).

User demand usually concerns 1) locating vine plots and 2) identifying some characteristics that can be connected to cropping practices or crop quality (interrow width, orientation of rows, presence of grass between rows. . . ).

Most vineyard related studies using remote sensing data meet the second requirement by detecting vine rows (Bobillet *et al.*, 2003) for example, or by characterizing training mode (Wassenaar *et al.*, 2002) or foliar density (Hall *et al.*, 2003) for previously delimited plots. Those dealing with vineyard plots identification and delineation often use multi-spectral information on over-metric spatial resolution images, provided by satellites Landsat, Ikonos or airborne sensors (Rodriguez *et al.*, 2006; Johnson *et al.*, 2001; Gong *et al.*, 2003). However, the increasing availability of Very High Spatial Resolution (VHSR) images offers a lot of new potential applications: the object shape and spatial structure are becoming more distinguishable, providing greater discrimination and characterization opportunities. Indeed, according to the Shannon-Nyquist theorem<sup>1</sup>, periodic patterns resulting from the spatial arrangement of vine plants (often in lines or grid), become perceptible with a spatial resolution that is at least twice as small as the pattern period.

---

<sup>1</sup>See any book on signal processing for more information about this theorem

In the study area, like in many wine-growing regions, the minimum distance between two vine rows, is about 1.5 m; consequently, image spatial resolution should be lower than 0.75 m. However, as they deal with spatial structures or shapes, these new applications also require new image processing approaches.

in: International Journal of Remote Sensing, Vol. 29, n° 4, 2008

In a recent study (Warner *et al.*, 2005), a classification algorithm based on an analysis of autocorrelograms was developed and tested using Ikonos panchromatic imagery of Granger (Washington). This method, although providing good results in the application presented, could hardly be generalized in older European wine-growing regions where the heterogeneity among researched patterns is high. Because of the periodic organization of vineyards, frequency analysis appears as a suitable approach for vine detection. Wavelet analysis presented in (Ranchin *et al.*, 2001) is applied to 25 cm resolution images for vine/non-vine pixel classification. Using a plot basis validation, 78 % of plots were accurately classified; but this approach is complex and needs significant user intervention. A Fourier Transform based analysis should be more straightforward and quite as effective since this tool is perfectly suited for oriented and periodic texture detection. Its efficiency has been demonstrated to characterize and monitor natural periodic vegetation (Couteron and Lejeune, 2001; Couteron, 2002). Wassenaar (Wassenaar *et al.*, 2002) successfully used it for vine/non-vine classification and characterization of previously delimited plots on 25 cm resolution images. On a sample of 46 ‘extremely varied field patterns’, vine/non vine classification was correct for all the plots and only five errors were encountered concerning training mode classification of the 41 vine plots. Moreover, this method gave a very precise (less than 1 % error) estimation of interrow width and row orientation. Prat (Prat, 2002) employed a similar method to identify vine plots in an image. This one was first divided into small square windows (of 12.5 m side) on which five indices were deduced from Fourier spectrum and image radiometry. Then, a multidimensional supervised classification using maximum likelihood led to correct classification of 81 % of vine pixels.

Other very popular approaches for textural analysis are based on Haralick’s researches, according to whom ‘the texture information in an image is contained in the overall or “average” spatial relationship which the gray tones in the image have to one another’ (Haralick *et al.*, 1973). He then introduced the ‘gray-level spatial dependency’ (cooccurrence) matrices, which had remained unused for many years as they were too time-consuming. With the amazing increase of computer power, cooccurrence became one of the most popular characterization tools because it is based on second order statistics, well suited for the description of textural properties, which the human eye is most sensitive to. A lot of studies have demonstrated its relevance for textural analysis (Chen *et al.*, 1979) and its usefulness for many applications: urban planning (Morales *et al.*, 2003), medicine (Smutek *et al.*, 2003), scientific police (Verma *et al.*, 2002), textile industry (Abdulhady *et al.*, 2002)... and even remote-sensing for agro-forestry (Arvis *et al.*, 2004).

The general objective of this work was to develop an automatic method for vineyard detection and characterization using very high spatial resolution remote-sensing data and without any a priori knowledge of the parcel plan. Indeed, this latter is not available in most European wine-growing regions and, when a georeferenced cadastre is available, it generally does not correspond to agricultural plots actually observable in the field. To foster large-scale applications, image used was a ‘standard’ orthophotography in natural colour, with a 50 cm spatial resolution, similar to data available on the whole French territory. In this paper, the relevance of cooccurrence based analysis is evaluated in comparison with a frequency approach to meet the need for vine plot detection. Moreover, characterizations of row orientation and/or interrow width, deduced from these approaches, are compared.

## 2 Study area

The study area is part of the La Peyne watershed (110 km<sup>2</sup>) and is located in the Languedoc-Roussillon region - France (Figure 1). This zone is representative of the French Mediterranean coastal plain with respect to geology, agricultural practices and vineyard management (Wassenaar *et al.*, 2002). Two subsets, of 2 km<sup>2</sup> and 1 km<sup>2</sup>, have been selected from this area near Roujan municipality (43° 30’N, 3° 18’E). Despite a general decrease, vine cultivation is still predominant and covers about 70 % of the 271 plots of the study area.

The diversity of agricultural practices in the study area leads to a great heterogeneity among vine plots (difference of vigour, grass between rows, missing vine trees...) which generally hampers the use of

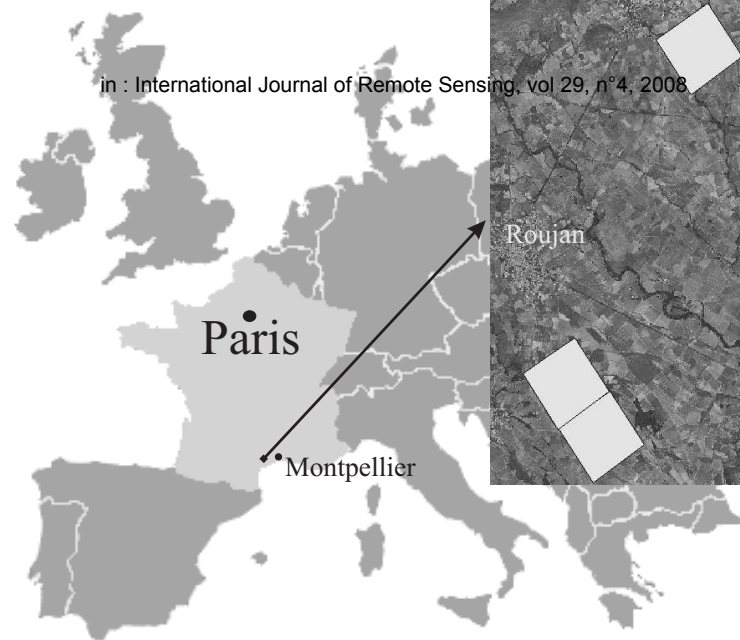


Figure 1. Localization of the study area in France and Europe.

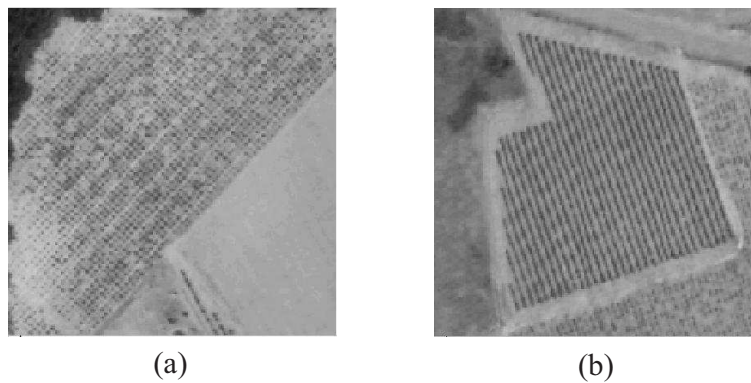


Figure 2. Vine training modes: a) Goblet (grid pattern), b) Trellis (row pattern).

spectral information for vineyard detection. However, on VHRS remote sensing data, two main patterns can be observed according to training mode (figure 2):

- Grid pattern: about a quarter of the vineyard considered in this study is trained as ‘goblet’. This old method of vine training involves no wires or other system of support: vine stocks are planted according to a grid pattern, often square, with approximately  $1.5 \text{ m} \times 1.5 \text{ m}$  spacing in the study area but sometime up to  $3 \text{ m}$  spacing in dry regions.
- Line pattern: most of the recent vineyards are trained using horizontal wires to which the fruiting shoots are tied. Spacing separating two wires is higher than spacing between vine stocks guided by the same wire (often  $1 \text{ m} \times 2.5 \text{ m}$  spacing in the study area), which leads to row patterns. More adapted to mechanization, this training mode named trellis or wire-training, is mainly used.

These patterns can be observed on each spectral band and are less dependant on the previously cited heterogeneities. Then, with vineyard detection in aim, methods should be more robust when dealing with textural aspects than spectral ones.

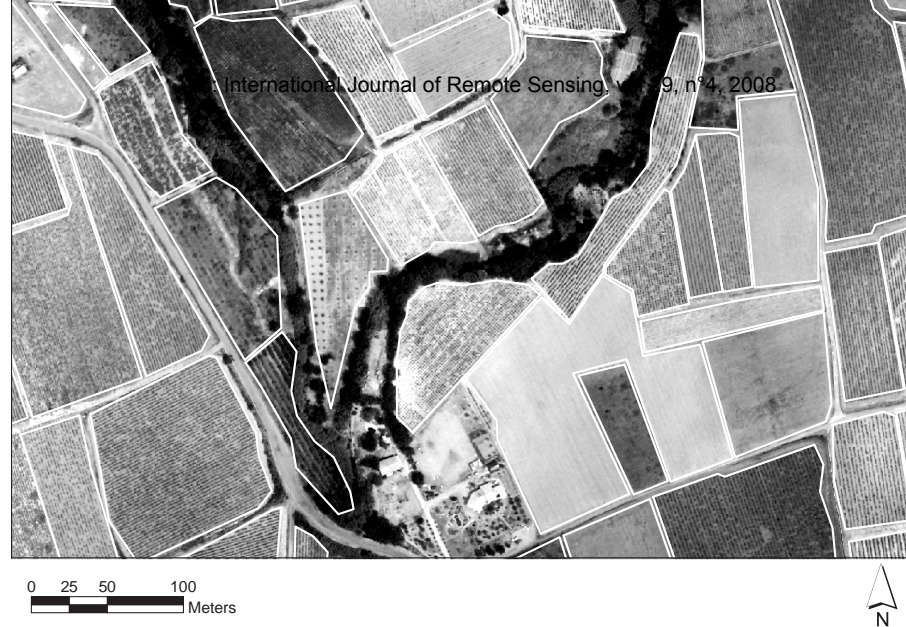


Figure 3. Zoom on the study area. All the plots of the study area have been surveyed and integrated with their characteristics in a geodatabase.

### 3 Data acquisition

Data acquisition was made during the first week of July 2005, when foliar development was such that both vine and soil were visible on aerial photographs. A digital camera was used aboard an Ultra Light Motorized (U.L.M.) to acquire photographs in natural colours (Red, Green and Blue). Images were geometrically corrected and georeferenced using ArcGis<sup>®</sup> (ESRI), mosaicked using ERDAS<sup>®</sup> Imagine (Leica Geosystem) and resampled to a 50 cm resolution. The resulting images have characteristics similar to those of the BD-Ortho<sup>®</sup> coverage of the French geographic institute (IGN), which is widely used and covers almost all the French territory.

For result validation, ground-truth information was collected at the same time as image acquisition. Each of the 271 vine and non-vine plots of the site has been digitized in a GIS database (figure 3) which also contains information concerning land use and a series of characteristics for vine plots: training mode, interrow width, orientation, rough estimates of vine height and width, soil surface condition... Row orientation and interrow width were obtained by precise on-screen measurements: row orientation was measured with a 1° precision and interrow width was calculated by dividing the width of the whole plot by the number of interrows.

### 4 Textural analysis methods

Both methods compared in this paper were implemented to calculate textural characteristics on the surrounding of each pixel using a sliding window.

#### 4.1 Cooccurrence analysis: use of Haralick's contrast feature

The first method presented in this study has been developed from cooccurrence matrices defined in (Haralick *et al.*, 1973). Element  $p_{i,j}$  of each matrix  $P_{d_x, d_y}$  contains the number of transitions from grey level  $i$  to  $j$  between two pixels of image  $I$ , distant from  $d_x$  pixels in column and  $d_y$  in line (equation 1):

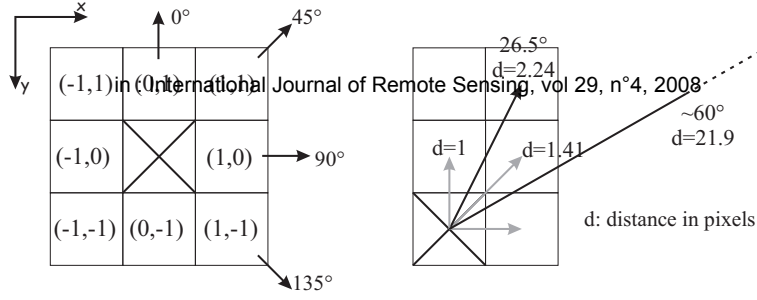


Figure 4. Cooccurrence calculation distances vs orientations. Left: nearest neighbours. Right: more orientations implies longer calculation distances (greater than interrow widths).

$$p_{i,j} = P_{d_x,d_y}(i,j) = \# \left\{ ((x,y), (x',y')) \mid x' = x + d_x, y' = y + d_y; \right. \\ \left. (I_{x,y} = i \ \& \ I_{x',y'} = j) \ \text{or} \ (I_{x,y} = j \ \& \ I_{x',y'} = i) \right\} \quad (1)$$

where  $\#$  denotes the number of elements in the set and  $I_{x,y}$  is the grey level of pixel of coordinate  $(x,y)$ . Each cooccurrence matrix is then symmetric and for a  $N_g$  grey level image, its size is equal to  $N_g \times N_g$ .

Depending on the spatial resolution used (50 cm) and row spacing encountered (from 1.4 m to 2.5 m) analysis must be done on transitions between one pixel and its direct neighbours in order to characterize soil-vine transition:  $|d_x|, |d_y| \in \{0, 1\}$ . Only four directions are then explored:  $\theta = 0^\circ, 45^\circ, 90^\circ$  or  $135^\circ$ . With image coordinates increasing from upper left to lower right corner:  $d^0 = (d_x, d_y) = (0, -1)$ ,  $d^{45} = (1, -1)$ ,  $d^{90} = (1, 0)$  and  $d^{135} = (1, 1)$ . Search for more directions would imply longer calculation distances, unsuited to interrow widths (figure 4).

From cooccurrence matrices, Haralick defined 14 textural characterization features, some of which being correlated. As preliminary comparative analysis (unpublished), they have been computed on a sliding window applied on a synthetic image imitating 3 vine plots (with row oriented at  $0^\circ, 45^\circ$  and  $90^\circ$ ) as well as a non-vine plot, modeled by a random texture. Some features (e.g. correlation or angular second moment) could be used to highlight vine plots, but their histogram have a high dispersion, which would hamper a good pixel classification in vine/non-vine. That is not the case for contrast feature (equation 2), which appeared to be well suited for vineyard detection. The higher the local variations in the sliding window, the higher the contrast, strongly depending on orientations of both vine row and feature calculation. Consequently, contrast is high when calculated in a direction that is perpendicular to vine rows and very low when calculated in row direction.

$$f_2(P_{d_x,d_y}) = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{|i-j|=n} p_{i,j} \right\} \quad (2)$$

We then propose a ‘vine index’ based on this property, which can be used to distinguish row patterns from other non-oriented high contrasted patterns (e.g. checkerboard-like). Indeed, vineyard will be characterized by a high difference of contrast calculated in two perpendicular directions. For each pixel, signed differences between the four pairs of perpendicular directions are compared. The highest difference is the vine index and the two directions associated provide a class of row orientation to the focal pixel. Theoretically, when calculated on vineyards with row orientation  $\theta \in [23, 68]$ , contrast should be high for direction  $d^{135}$  and low for  $d^{45}$ , so that these vineyards should be classified in class  $C_{45}$ ; likewise, class  $C_{90}$  corresponds to vine row orientations in  $\theta \in [69, 112]$ ,  $C_{135}$  to  $\theta \in [113, 158]$ , and  $C_{180}$  to  $\theta \in [158, 180]$  or  $\theta \in [1, 23]$ . Contrast is all the more interesting as it can be computed directly on image without previous calculation of cooccurrence matrices; this considerably reduces calculation time. Figure 5 describes the classification method applied on a synthetic image.

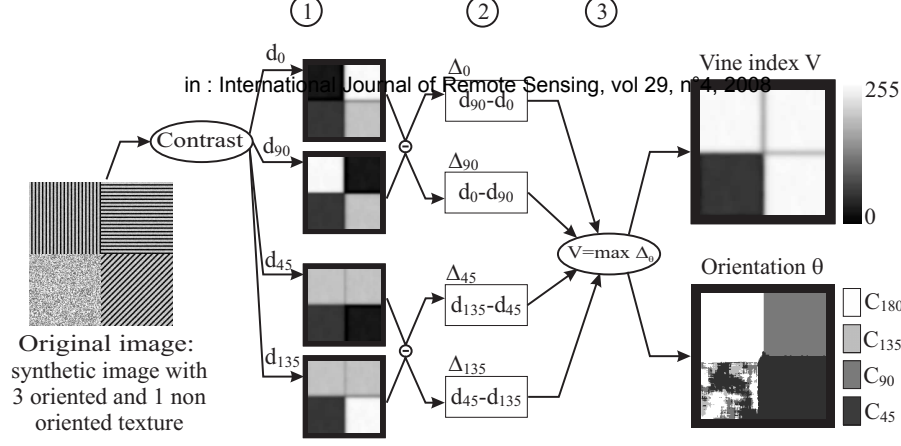


Figure 5. Vineyard detection using Haralick's contrast. 1) Contrast calculation on sliding window in orientations: 0°, 45°, 90° and 135°. The brighter the pixel, the higher the contrast. 2) Difference of contrast between two orthogonal directions. 3) The maximum value of the differences gives the 'vine index' and an estimation of row orientation with a classification in four classes.

#### 4.2 Frequency analysis: use of local Fast Fourier Transform

The second method developed in this study is based on the works of (Wassenaar *et al.*, 2002) who used the Fourier Transform to characterize already delimited plots. Here, we test the same kind of approach when the only available data is the aerial image (the main goal being vineyard detection).

Fourier theory states that almost any signal, including images, can be expressed as a sum of sinusoidal waves oscillating at different frequencies. The discrete Fourier transform (FT) of an image is computed using the Fast Fourier Transform (FFT) algorithm. Taking the modulus of the complex-valued FFT results yields the FT amplitude (or spectrum), which can be represented in the frequency domain as an image of the same size as the initial image,  $I$ . In the conventional representation, this image is symmetric with respect to its centre, which contains the average of  $I$  i.e. the amplitude of the null frequency  $F_0$ . Each pixel corresponds to a particular spatial frequency increasing the further it is from centre. Its value codes the amplitude of Fourier spectrum, which depends on the frequency presence in image  $I$ . The amplitude of the discrete Fourier Transform of  $I$  is defined by equation 3:

$$a(u, v) = \left\| \frac{1}{N_x N_y} \sum_{x=0}^{N_x-1} \sum_{y=0}^{N_y-1} I_{x,y} \exp \left[ -j2\pi \left( \frac{ux}{N_x} + \frac{vy}{N_y} \right) \right] \right\| \quad (3)$$

where  $(N_x, N_y)$  is the size (column, line) of both images,  $x = 0 \dots N_x - 1$ ,  $y = 0 \dots N_y - 1$  are spatial indexes (in image  $I$ ) and  $u = 0 \dots N_x - 1$ ,  $v = 0 \dots N_y - 1$  are frequency indexes (in the Fourier spectrum).

The method consists in applying the FFT algorithm on a sliding window. When this window contains vineyard arranged in rows, two peaks will be present on the Fourier image, and will be symmetric with respect to the centre; for the grid pattern of a goblet vine, four peaks will be present at 90° (see figure 6). The FFT algorithm assumes that the data is periodical, i.e. the image repeats from end to end infinitely. Therefore, FFT calculation on a finite window may lead to aliasing artefacts (Gibbs' phenomenon) when pixel values at the edges of the window do not match. To avoid these artefacts, which could introduce additional peaks, pixel values are first of all multiplied by a Hanning window (by Von Hann) which shape is half a cycle of a cosine wave and is null at the edges (see figure 7). Three characteristics can be deduced from the peak value and position:

- The distance  $r$  of the peaks from the image centre corresponds to the pattern frequency in the window and, consequently, is connected to the vineyard interrow width, which is equal to the size  $N$  of the sliding window divided by  $r$ . Peaks can then be sought in an annular ring, corresponding to potential vineyard interrow widths to avoid confusion with other periodic patterns (e.g. orchards, characterized a by larger interrow).
- The angle  $\theta$ , between horizontal line and one peak, determines the wave direction in a polar coordinate

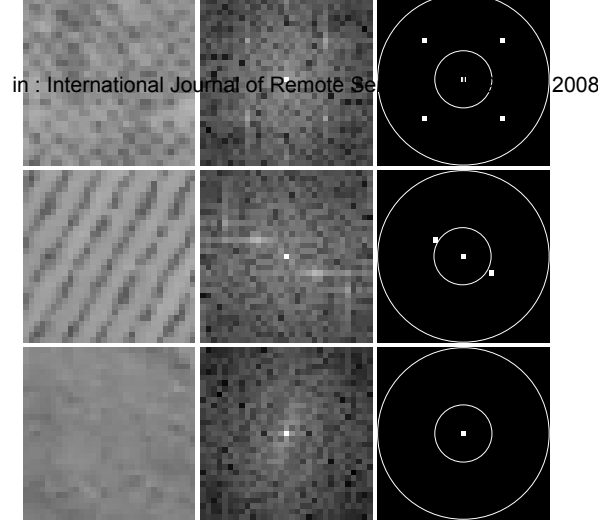


Figure 6. Examples of Fourier Transform. The left-hand side shows 3 images, which are the same size as the sliding window, extracted from a goblet vine (up), a trellis vine (middle) and a non-vine (down); the centre shows their respective Fourier Transform and the right-hand side shows the frequencies remaining after thresholding (the same threshold is used for the three images).

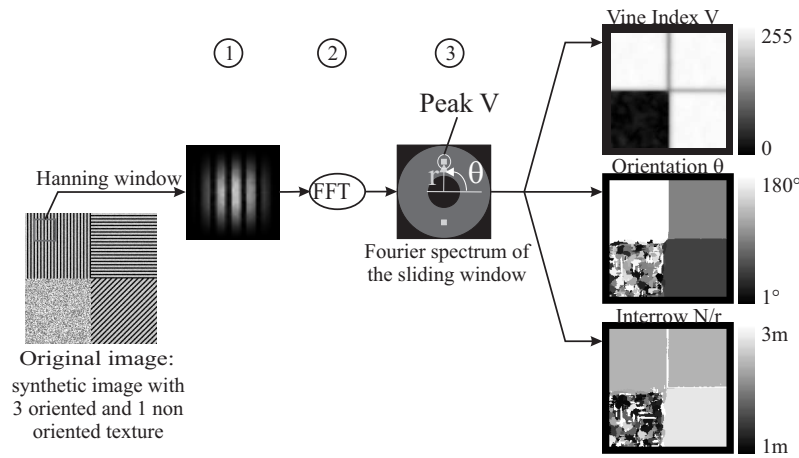


Figure 7. Vineyard detection using Fourier Transform (FT). 1) Use of a Hanning sliding window of size  $N \times N$ . 2) FT calculation on the window. 3) Search for the maximum FT amplitude among the potential vineyard frequencies; for each pixel, this value is saved as 'vine index' and its position gives row orientation and interrow width.

system, which is equal to row direction in a geographical coordinate system ( $90^\circ$  offset).

- Peak amplitude is the 'vine index': the higher the amplitude, the higher the probability of the window being in a vineyard.

## 5 Implementation of the textural analysis methods

Both methods were implemented in C language and applied on the study area.

A sensitivity analysis to the window size has been carried out since accuracy of detection and characterization depends on the number of pixels in the window. On one hand, this window must be large enough to take into account the repetition of row or grid patterns, so a large window provides more precise information when located inside a plot. On the other hand it decreases classification results near plots boundaries as it can contain several patterns at the same time, and of course, increases the calculation times. Eight window sizes have been tested from  $11 \times 11$  to  $39 \times 39$  pixels. For the frequency based method, results become acceptable for a  $27 \times 27$  window size. (13% of badly classified pixels) and the lowest rate of misclassification (12.2%) is reached for  $31 \times 31$ . Extending window size up to  $39 \times 39$  pixels does not improve results (12.4%



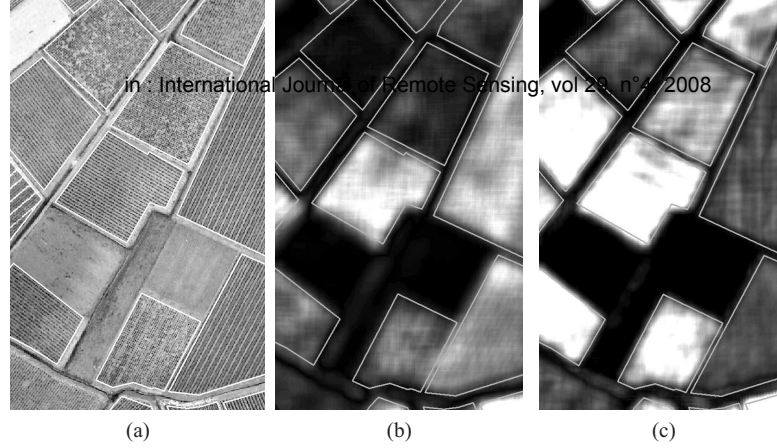


Figure 8. Results on a subset of the study area. a) original image, b) vine-index issued from the contrast method, c) vine-index issued from the frequency method. The manual segmentation is superposed in grey on each image.

of misclassified pixels) while doubling computational time. Consequently, the best trade-off for the window size is about  $31 \times 31$  pixels, which can contain from five to ten vine rows in the study area. Through visual assessment of the different window sizes, this latter also appears to be the best for the contrast approach.

The methods have been tested on each of the three channels of the image. Vine index, produced by both methods, is an indicator of the probability for a pixel to belong to a vineyard. For vineyard detection, a threshold has been defined to separate two classes: ‘vine’ and ‘non vine’. The pixels whose vine index is lower than the threshold are classified as ‘non vine’, the others as ‘vine’. Threshold determination is often empirical; here, it was chosen to minimize global classification error for a representative sample of the database plots. Therefore, omission error (vine detected as non vine) is chosen lower but almost equal to commission error (non vine detected as vine). Some tests have shown that a sample containing 10 % of the plots was large enough to determine a threshold value that is very close to the one obtained using all the plots. The sample must be representative enough of the study area, particularly in terms of land use and vineyard training mode.

## 6 Validation method

Validation is performed on a plot basis using all the 271 vine and non-vine digitized plots of the study area. A simple classification rule is employed: a plot is classified as ‘vine’ if at least 75 % of its pixels are ‘vine’, as ‘non vine’ if at least 75 % of its pixels are ‘non vine’ and not classified otherwise. Then, vine plot characteristics (orientation class obtained by Haralick’s contrast and orientation and interrow width given by Fourier Transform) are chosen to be the majority value among the pixels of the plot. For validation, results of plot classification and characterization are compared to the information contained in the ground-truth database.

## 7 Results

Best results were obtained with the Red channel, probably because it provides the highest contrast between vine and soil surface, even when covered by grass. Therefore, we only present results derived while using this channel. Figure 8 shows vine-index of both methods on a subset of the study area.

### 7.1 Classification results

Table 1 gives confusion matrices which enable the estimation of plot classification quality by comparing it to ground truth data. Considering both vine and non-vine plots, 70.8 % of the 271 plots are well-classified with contrast method and 86 % with frequency method.

Table 1. Confusion matrices (row: ground truth, column: methods). Classification in % of the 190 vine and 81 non vine plots using Red channel: a plot is well-classified if at least 75 % of its pixels are well-classified, badly classified if less than 25 % of its pixels are well-classified, not classified otherwise.

in: International Journal of Remote Sensing, vol 29, n°4, 2008								
	CONTRAST METHOD				FREQUENCY METHOD			
	vine	non vine	not classified	Total	vine	non vine	not classified	Total
Vine	72%	7%	21%	100%	89%	5%	6%	100%
Non vine	1%	68%	31%	100%	2%	79%	19%	100%

Because of the threshold chosen, both methods lead to a worse classification for non vine than for vine plots. The main cause of non detection is when the vine is too young i.e. less than three years old. Vegetation is thus not sufficiently developed for the rows to be visible on aerial photographs; consequently, these vine plots have good classification rates of only 26 % and 47 % for contrast and frequency methods respectively (see figure 9b for an example).

Globally, results provided by contrast method are poorer than those provided by frequency method. For non vine plots, one explanation may be that contrast does not take into account the periodicity of patterns: a road, for example, can lead to a difference of contrast in two orthogonal directions that is as high as that of a vine but does not have a peak of frequency corresponding to vine interrow width. Figure 9a shows an example of non vine detected as vine by contrast method but not by frequency method. Likewise, confusion could theoretically appear between vine and orchards. However, since the sliding window size is adapted to vineyards interrow widths, vine index will be lower on orchards because their interrow widths are much larger.

For vine plots, results must be analyzed according to training mode. Indeed, goblet vines benefit from a good classification rate of only 49 % using contrast method against 89.7 % for ‘adult’ trellis vines (all goblet vines are adult). Likewise, frequency method leads to a good classification rate of 88.6 % for goblet vines and 95.7 % for ‘adult’ trellis vines.

For both methods, the poorer results obtained for goblet vines mainly have two origins which lead to a low visibility of soil between rows. Firstly, goblet vines are not stressed by wires and can grow freely in all directions; secondly, interrow widths of goblet vines are generally smaller than those of trellis vines (on the study area, 67 % of the goblet vines have an interrow width lower than 160 cm against only 2 % of the trellis vines).

Concerning goblet vine classification, the big difference (39.6 %) between methods is due to the fact that goblet vines are often planted on a square grid so that contrast is identical in both perpendicular directions, which hamper detection by the contrast method (see figure 9c for example). In fact, most goblet vines properly identified by the contrast method are pruned along one direction, which leads to a higher contrast in the perpendicular direction.

## 7.2 Results of vine plot characterization

Estimation of orientation and interrow width obtained by both methods are now examined.

With the contrast method, 78 % of the plots correctly classified as vine have been allocated with the correct orientation class (among the four used). As evoked previously, defining more than four orientation classes cannot be considered with this resolution because it would imply, for contrast calculation, a distance too large in front of interrow width (figure 4). Indeed, if a 30° class is sought, the distance in pixels needed to compute contrast feature will be at least  $(d_x, d_y) = (5, 3)$  i.e. an Euclidian distance of about 2.9 m (for 30.96° and 10.98 m for 30.07°), larger than most of interrow width.

Figure 10a shows characterization results for well classified vine plots, using frequency method. Fourier Transform leads to more accurate results for vine row orientation. Indeed, between on-screen measurements and method estimation, an average absolute difference of 3.5° was found, which is less than a 2 % error. Moreover, error distribution is almost centered (figure 10b).

Interrow width calculation is also very precise with an average absolute difference of 6.2 cm, i.e. about 3 % error (see figure 10d for error distribution). The four outliers shown in figure 10c, concern two vine plots covered by grass only one interrow out of two, which leads to a pattern period twice as large as

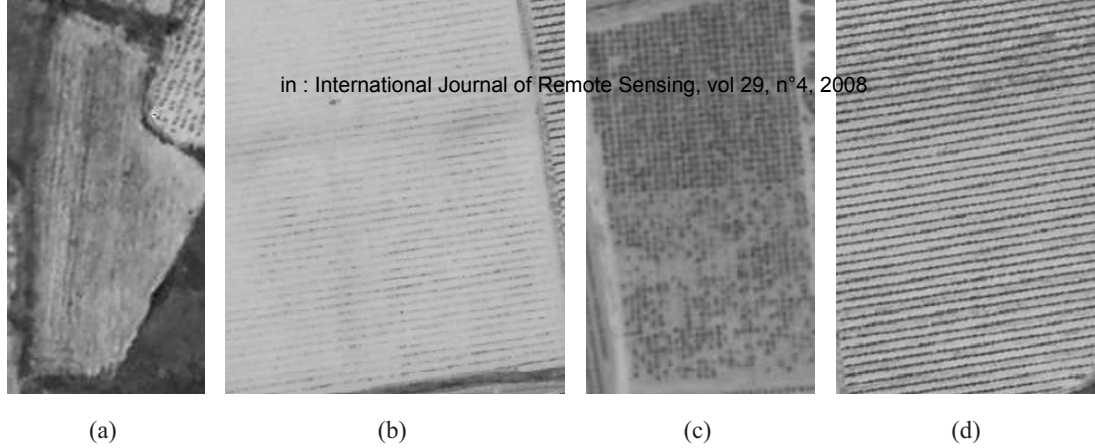


Figure 9. Examples of plots. a) Non cultivated plot recognized as vine by contrast method: an oriented pattern is visible but with no particular frequency. b) Very young trellis vine, badly classified by both methods: rows are hardly visible. c) Goblet vine classified as non vine by contrast method and well-classified (with 98 % of pixels) by frequency method. d) Trellis vine, well classified by both methods.

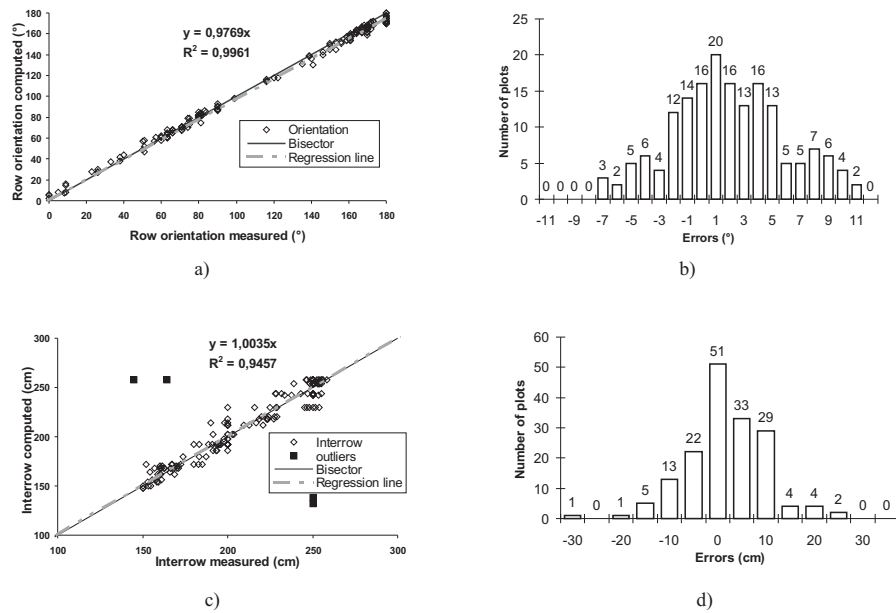


Figure 10. Orientation and interrow characterization using frequency method. Right: comparison of retrieved characteristics and plot measurements; regression and bisector lines are almost confounded. Left: error distributions.

interrow width, and two vine plots ploughed between rows, for which interrow width determined is half on-screen measurement. Characterization results highly depend on the size of the calculation window (see below), which is why (Wassenaar *et al.*, 2002), who applied the FFT algorithm on the entire plot, obtained 1 % errors for both orientation and interrow width.

## 8 Conclusion and discussion

Two methods were compared for vineyard detection and characterization from aerial photograph presenting ‘standard’ characteristics. The first one was based on Haralick’s cooccurrence analysis, which had been successfully tested on many applications but not yet for vineyard detection. The second one was based on Fourier analysis, a well-tried approach for periodic and oriented pattern recognition.

The originality of the proposed cooccurrence approach lies in the comparison of the contrast feature calculation in two orthogonal directions. However, this method leads to a poorer vine/non-vine classification

than with the frequency method mainly for two kinds of plots:

- non-vine: contrast is sometimes higher in one direction than for its perpendicular, due to ploughing or roads for example, and this leads to a classification as 'vine' of 32 % of non-vine plots. However, the resulting patterns have no particular frequency and are globally well-classified by frequency method (21 % of commission error).
- Goblet vines: with this training mode, when there is no privileged direction of pruning, contrast is the same in both perpendicular direction, which leads to a 'non-vine' classification of 51 % of goblet vines. On the contrary, since their overall pattern is periodic, these plots are well-classified with the frequency method (only 21.4 % of error).

The poorer results of goblet detection using both methods are strongly linked to the relation between the pattern period (interrow width) and the image resolution: the limit of the Shannon-Nyquist theorem is reached. However, this highlights the fact that a coarser resolution could be used in many other wine-growing regions, especially dry ones such as Castilla-la-Mancha in Spain, where interrow widths are up to three meters. These approaches could also be applied to orchards with other resolutions as long as the periodic pattern is visible.

In comparison with the contrast method, the frequency approach not only permits a better 'vine'/'non-vine' classification (86 % against 70 %), but also a very precise estimation of row orientation and interrow width (2 % and 3 % errors respectively) whereas only four classes of orientation could be defined and distinguished with an accuracy of 78 % using the contrast feature.

In addition to the utility of characterization as such, orientation and interrow width estimation could be used to increase plot classification quality in prospect for a segmentation stage. On the one hand, they could be used to better separate detected plots; indeed, some plots, which are spatially very close, would be grouped within a same polygon unless they have different row orientation or interrow width. On the other hand, these characteristics could help the discrimination of badly classified non-vine plots; indeed, vine classified plots with no particular orientation or interrow width could be reclassified as non-vine.

In prospect, to meet the second user requirement, characteristics of row orientation and interrow width could also be used for an automatic detection of each vine row. This would enable the evaluation of more vineyard characteristics such as missing vine trees or soil surface condition (e.g. presence of grass between rows). Moreover, vine index could also be used on vine plots as an indicator of vine quality, since its intensity depends on the pattern contrast.

## Acknowledgements

This work is part of two projects: BACCHUS European Project (<http://www.bacchus-project.com>) and MOBHYDIC project of the French national program of research in hydrology (PNRH). The authors thank C. Debain (CEMAGREF) for his contribution concerning the cooccurrence approach.

We wish to pay tribute to the late J.M. Robbez-Masson who died in a mountain accident. We are deeply grateful for his kindness, availability and for the very constructive discussions we shared with him concerning this work at meetings and on field trips.

## References

- ABDULHADY, M., ABBAS, H. NASSAR, S., 2002, Fabric fault classification using neural trees. *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics*, **6**, 114–117.
- ALONSO, F., ALGORRI, M.E. FLORES-MANGAS, F., 2004, Composite index for the quantitative evaluation of image segmentation results. *Proceedings of the 26th Annual International Conference of the IEEE EMBS*, San Francisco, USA.
- ARVIS, V., DEBAIN, C., BERDUCAT, M. BENASSI, A., 2004, Generalization of the cooccurrence matrix for colour images: application to colour texture classification. *Image Analysis and Stereology*, **23**, 63–72.
- BOBILLET, W., DA COSTA, J.-P., GERMAIN, C., LAVIALLE, O., GRENIER, G., 2003, Row detection in high

- resolution remote sensing images of vine fields, *European Conference on Precision Agriculture, Berlin*, 81–87.
- CHEN, P.C. PAVLIDIS, T., 1979, Segmentation by texture using a co-occurrence matrix and a split-and-merge algorithm, *Computer Graphics and Image Processing*, **10**, 172–182.
- COUTERON, P., 2002, Quantifying change in patterned semi-arid vegetation by Fourier analysis of digitised air photographs, *International Journal of Remote Sensing*, **23**, 3407–3425.
- COUTERON, P. LEJEUNE, O., 2001, Periodic spotted patterns in semiarid vegetation explained by a propagation-inhibition model, *Journal of Ecology*, **89**, 616–628.
- GONG, P. MAHLER, S.A., BIGING, G.S. NEWBURN, D.A., 2003, Vineyard identification in an oak woodland landscape with airborne digital camera imagery, *International Journal of Remote Sensing*, **24** (6), 1303–1315.
- HALL, A., LOUIS, J., LAMB, D., 2003, Characterising and mapping vineyard canopy using high-spatial-resolution aerial multispectral images, *Computers and Geosciences*, **29**, 813–822.
- HARALICK, R.M., SHANMUGAM, K., DINSTEN, I., 1973, Textural Features for Image Classification, *IEEE Transaction on Systems, Man, and Cybernetics*, **3** (6), 610–621.
- JOHNSON, L.F., ROCZEN, D., YOUKHANA, S., 2001, Vineyard canopy density mapping with Ikonos satellite imagery, *Presented at the Third International Conference on Geospatial Information in Agriculture and Forestry*, Denver (Colorado), 5–7 November 2001.
- MORALES, D.I., MOCTEZUMA, M., PARMIGGIANI, F., 2003, Urban and Non Urban Area Classification by Texture Characteristics and Data Fusion, *International Geoscience and Remote Sensing Symposium (IGARSS)*, **6**, 3504–3506.
- PRAT, S., 2002, Caractérisation de végétations régulières par télédétection à très haute résolution spatiale: Application à l'analyse texturale de parcelles viticoles, *DESS Statistique et Traitement du Signal*, Université Blaise Pascal, Clermont-Ferrand.
- RANCHIN, T., NAERT, B., ALBUISSON, M., BOYER, G., ASTRAND, P., 2001, An Automatic Method for Vine Detection in Airborne Imagery Using Wavelet Transform and Multiresolution Analysis, *Photogrammetric Engineering and Remote Sensing*, **67** (1), 91–98.
- RODRIGUEZ, J. R., MIRANDA, D., ALVAREZ, C. J., 2006, Application of Satellite Images to Locate and Inventory Vineyards in the Designation of Origin "Bierzo" in Spain, *America Society of Agricultural and Biological Engineers*, **49** (1), 277–290.
- SMUTEK, D., ŠÁRA, R., SUCHARDA, P., TJAHHADI, T., ŠVEC, M., 2003, Image texture analysis of sonograms in chronic inflammations of thyroid gland, *Ultrasound in Medicine and Biology*, **29** (11), 1531–1543.
- VERMA, M.S, PRATT, L., GANESH, C., MEDINA, C., 2002, Hair-MAP: A prototype automated system for forensic hair comparison and analysis, *Forensic Science International*, **129** (3), 168–186.
- VINCINI, M., FRAZZI, E., Assessment of erosion-related vineyards features in Tuscany by object-oriented classification of high resolution images *Proceedings of Agro Environ 2004*, 20–24, October 2004, Udine (Italy).
- WARNER, T.A., STEINMAUS, K., 2005, Spatial classification of orchards and vineyards with high spatial resolution panchromatic imagery, *Photogrammetric Engineering and Remote Sensing*, **71** (2), 179–187.
- WASSENAAR, T., ROBBEZ-MASSON, J.-M., ANDRIEUX, P., BARET, F., 2002, Vineyard identification and description of spatial crop structure by per-field frequency analysis, *International Journal of Remote Sensing*, **23** (17), 3311–3325.
- WASSENAAR, T., ANDRIEUX, P., BARET, F., ROBBEZ-MASSON, J.-M., 2005, Soil surface infiltration capacity classification based on the bi-directional reflectance distribution function sampled by aerial photographs. The cases of vineyards in a Mediterranean area, *Catena*, **62**, 94–110.