VINEYARD SPATIAL STRUCTURE ANALYSIS BY PER-FIELD AERIAL PHOTOGRAPH PROCESSING

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ABSTRACT

Hydrological catchment studies have demonstrated the dominant influence of soil surface condition and field structure on rainfall and pollutant runoff in the Mediterranean viticultural environment. Recognising these parameters at the scale of one or more catchments is essential for the comprehension of phenomena like rivers in spate and agricultural pollution, as well as for a good water resource management.

Based on very high spatial resolution data (0.25 m), a method is developed to provide detailed quantitative information on spatial crop structure by analysis of stationary spatial frequencies. A simple crop geometry model, based on general knowledge and field observations, is applied to the Fourier power spectrum of aerial imagery obtained over the La Peyne valley (Hérault, France). By doing this on a per-field basis, using a digital land register map, vineyards can be identified and within-field constant vine frequencies can be extracted. Analysing these frequencies, per-field information on crop spacing, orientation and training mode are provided. The results are directly written to a GIS database, without creation of an intermediate image layer.
Highly accurate crop structure data were obtained, independent of the very variable soil surface radiometry and its spatial structure. Main vineyard training modes, goblet and wire-trained, as well as orchards and continuous crop/fallow fields were generally well classed.

1. INTRODUCTION

Hydrological catchment studies have demonstrated the dominant influence of soil surface state and field structure on overland flow (Andrieux *et al.* 1996; Leonard & Andrieux 1998) and pesticide transport (Lennartz *et al.* 1997) in the Mediterranean viticultural environment. Recognising these surface variables at the scale of one or more catchments is mandatory for the comprehension of flooding events, agricultural pollution, and water resource management.
Up to now, little effort has been directed on the analysis of discontinuous crops such as vineyards using remote sensing. Most studies applied to vineyards exploit the spectral features of the radiometric signal, without paying attention to the spatial features (Wildman 1979; Minden & Philipson 1982; Trolier *et al.* 1989, using Landsat TM; Johnson *et al.* 1998). Hill (1994), used AVIRIS data in an environmental study to estimate at about the same spatial resolution (20×20m pixel) a rough soil erosion risk of Mediterranean vineyards using spectral unmixing techniques. Company (1994, 1995), using airborne SAR and ERS data to describe soil surface roughness under Mediterranean vineyards, was severely hampered by the effect of vinerows and their orientation on radar backscatter.
A recent study (Ranchin *et al.* 2000), took advantage of the spatial structure, using wavelet analysis on aerial imagery trying to delimit vineyards for evaluating the European Community vineyard register. However, their method does not provide an equally satisfying result for the different training modes, nor a quantitative description of crop structure per field. Such description is required by environmental studies trying to quantify and map soil erosion risk at a catchment scale and monitor the effect of agricultural practice.
In the following an automated method is proposed to identify vineyards, providing detailed information on the spatial crop structure per field (planting pattern, spacing and orientation) on the basis of high spatial resolution data. The estimated surface variables could then be used as input to spatially distributed hydrological models.

2. STUDY AREA

2.1 Site description

Several sites were studied within the lower La Peyne watershed. La Peyne river is an affluent of the coastal river Hérault and located in the Hérault province, Southern France, about 60km west of Montpellier (43°37'N, 3°51'E). This catchment of about 70km^2, strongly dominated by vine cultivation (about 70% of the total surface), is representative of the French Mediterranean coastal plain with respect to geology, geomorphology, agricultural practices, vineyard management and vine species. The sites studied cover the variability in physical and viticultural conditions.

Apart from vine, some continuous crops like winter wheat and rape can be found. Fallow fields are frequently encountered, but more and more replanted with vine. Orchards occupy a special place in our study. They are rare and cover a very small area, but show similar spatial features to vineyards.

2.2 Mediterranean vine growing

The spatial structure of a vine cultivated landscape is very heterogeneous and dynamic. Vineyard fields in the coastal plain range in size from 0.05 ha to about 3ha, where the small ones occupy most of the surface. Every field is subject to different agricultural practices due to its location, water availability, orientation, vine species, site quality, farmer's conviction and many social and economic factors. This variety of practices includes within fields heterogeneity: rows can be grouped into blocks and soil in between rows in ploughed fields can selectively be left untouched.

The training mode of vines within a field is nearly as heterogeneous. Champagnol (1984) recognises nine main types of vine geometry, four of which are common to the Mediterranean region. From an hydrological point of view, three of these (cylinder, reversed cone and hemisphere) can be regrouped under the common name of 'goblet', i.e. individual plants distributed over a grid pattern without any guiding support. This is the traditional training mode throughout the Mediterranean region: a square grid with about 1.5×1.5m spacing, or slightly rectangular, i.e. 1.4×1.6m (Argillier 1989; Goma-Fortin *et al.* 1997). The other common spatial training mode is called 'wire-trained', i.e. rows of plants growing along two or more horizontal metal wires. The distance between the rows varies from 2.0 to 2.5m, depending a/o on water availability and height of the wire 'fences'. Distance between plants in a row is about 1.25m, but their wire-trained shoots provide a continuous cover along the wire. The orientation of the rows is related to exposition, but also to terrain morphology and field geometry. Actually being applied in somewhat more than half of the Mediterranean vineyards, the wire-training mode is being adopted more and more, because it allows mechanical harvesting. Nevertheless some private wine growers and even some wine co-operatives still prefer the goblet-mode.

3. DATA ACQUISITION

3.1 Spatial resolution

It follows from the previous description of the object of study, as well as the results of studies cited earlier, that the choice of the spatial resolution is critical. We actually need to spatially distinguish our objets, i.e. vine and underlying soil. The spatial resolution has to be in relation with the spatial frequency of the terrain (Curran 1999). As we know what frequencies we are looking for, statistical methods as proposed by Atkinson and Curran (1997) have not been considered. The optimal pixel size has to be lower than $1m^2$, i.e. the highest spatial resolution currently available from commercial space sensors (Allan 1996; Barnsley & Hobson 1996; Skidmore *et al.* 1997). Airborne photography still provides good performances because of the high resolving power of the photographic emulsion, and because of the flexibility of the device when using a 35mm camera to freely collect data in space and time at an acceptable cost.

To accurately locate vine plants (and so their spacing) as well as to be able to distinguish the sunlit soil surface under all geometric illumination and view conditions, the optimal spatial resolution was taken to be about 0.25×25m. This also meant to be a compromise between resolving power of the film and scanning resolution on one side and the geographical space covered (1.5 by 1km per picture) on the other, taking orthogonal pictures from a helicopter with a 35mm lens at 1100m above the surface.

3.2 Ground truth and GIS and image data

Photographs were taken from a Hughes 300 helicopter by a Canon EOS 500 camera with 35mm lens, using colour film. After scanning the images were processed using IDL/ENVI (Research Systems International, Boulder Colorado) software package. A ground team collected data on crop, training mode and soil surface condition for each field of all test sites (465 fields), which then were entered in a GIS database.

A topographic database obtained from IGN (French national geographic institute) and a 10m resolution DTM were used in georeferencing. Digitised land register maps were available and constitute an important input in the method developed.

For the moment the method has been applied to six image mosaics: data of all four test sites obtained at may 29th 1998 and data of two of these sites obtained one month later. The data presented in this paper are part of the calibration data set (one of the study sites at the first date), because the variability between the fields contained in this part well illustrates the properties of the procedure presented.

4. IMAGE PROCESSING STRATEGY

The objective of the study is to characterise the spatial pattern of fields, which additionally provides a way to discriminate vineyards from other crops. The technique is therefore based on the assumption that the training mode and its geometrical features are nearly constant within a field. Observations show that this assumption is generally well verified. To be able to identify the spatial features, the images offering the highest contrast between soil and vegetation have to be selected. The image processing approach will require:

1. for each field a unique or homogeneous result should be provided, allowing for classification as well as measuring of the spatial structure;
2. contrast invariance is required for a robust method, i.e. providing result independent of the underlying soil surface condition between and within fields, time of observation and geometrical position of the field in the image;
3. the feature extractor will have to be rotation invariant, but capable to capture the directional information;
4. scale has to be preserved, to be able to discriminate different structures on the basis of their known geometry, as well as to transform resulting pixel based parameters into distance;
5. shift invariance is required for the result not to be dependent upon the position of the structure with respect to the operator.

The red channel (from about 630 to 650nm for the film used) provides the best contrast between vine and soil surface (low reflectance of vegetation and high for mineral soil). Even if the soil surface is covered by grasses or residues of vine shoots, the surface signal remains higher due to a large portion of shadow contained in vine vegetation pixels.

A wide variety of mathematical approaches exist to analyse local spatial patterns: morphology analysis, edge analysis and frequency analysis. The first two groups are however of limited use, because they impose identification of the object (vine) before analysing it's shape and spacing. Moreover it is difficult to find texture descriptors that comply with the contrast invariance requirement. Further, the approach would have to be empirically tuned, and still problems would occur if for example lines in the image representing the vine rows are broken due to missing (groups of) plants in poorly managed vineyards.

Image texture analysis by it's spatial frequency distribution, offers a wide choice of texture descriptors. Periodic phenomena are best handled with the Fourier transform (Graps 1995) and allows for the use of knowledge-based criteria, but Fourier analysis is based on global information which is not adequate for the study of compact or local patterns. This is why Gabor (1946) introduced a local Fourier analysis, taking into account a sliding Gaussian window. This idea has recently been elaborated for use in industrial computer vision (Campbell & Murtagh 1998).

At the same time per-field analysis is more and more used in remote sensing studies (Mason *et al.* 1988; Smith *et al.* 1997) because of the development of GIS (Hinton 1996; Wilkinson 1996). The combination of local Fourier transform and per-field analysis appears to provide a pertinent solution to our problem. The Fourier power spectrum of each field has to be exploited using the knowledge based analysis to characterise each field's planting pattern, spacing and orientation.

5. MODEL DESCRIPTION

The model is schematically represented by a flow chart (figure 1). The different modules used by the model are commented below.

5.1 Field data extraction

Vector polygons representing the field limits need to be buffered for two reasons. First, field borders are not planted and so do not contain useful information. Second, the accuracy of the georeferencing has been evaluated to be about three meters on average with a considerable variation. To be sure not to include information from neighbouring fields and to minimise the border information, while maintaining enough

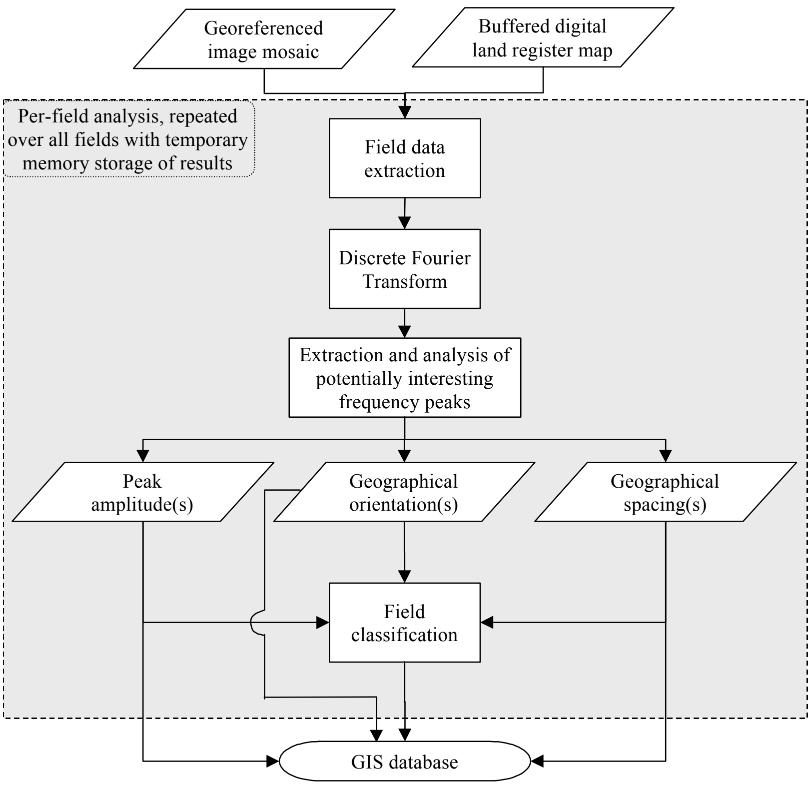

Figure 1 Flow chart showing the different procedure steps.

information for the smaller fields, a buffering of 7.5m was applied.
As the spatial context of the data needs to be preserved, the extracted pixels of a field are stored in a temporary matrix that constitutes an envelop of the field with zero data for non field pixels.

5.2 FFT

This matrix is then submitted to a discrete Fourier Transform, the Fast Fourier Transform (FFT) (Niblack 1986; Campbell & Murtagh 1998). The resulting power amplitude spectrum is defined by,

$$A(u,v) = \left\| \frac{1}{MN} \sum_{r=0}^{N-1} \sum_{c=0}^{M-1} f(r,c) \cdot \exp[-j2\pi \cdot (\frac{ur}{N} + \frac{vc}{M})] \right\| ,$$

where u=0,…,N-1, and v=0,…,M-1, are, respectively, the rowwise, and the columnwise frequency indices and r and c the corresponding row and column co-ordinates. This array is ordered in a traditional manner with the central element 0 containing the zero frequency component, F0. Pixels away from the centre represent increasing spatial frequency components of the image. In each dimension the position of these components is proportional to the size of the dimension. As this size can be expressed as a metric distance (number of pixels / pixel size = meters), frequencies and their orientation can be expressed in geographical space. Inversely we can determine annular rings or ellipses (for rectangular field envelops) as frequency filters whose width and eccentricity correspond to the frequency zones in which we expect to find the amplitude peaks corresponding to the objects of interest. This is schematically illustrated by figure 2 for a rectangular envelop matrix. The spacing criteria used for classification are a combination of standard knowledge and observations, because in reality transitional situations occur like when the vines of an originally goblet vineyard have been put on training wires for mechanical harvesting.

Conversely to the spacing criteria, the frequency amplitude criteria are not physically based. They have been obtained by calibration over a large range of fields, observed in the image under a range of viewing conditions. All 127 fields were used that could be extracted from an image mosaic of which a part is represented in the next chapter. The values found correspond to thresholds where the basis is a typical amplitude decay away from the centre of the Fourier power spectrum of a bounded variation image (Meyer 1992).
Orientation and spacing of the crop structure are computed from the frequency peaks retained. Together with the frequency peaks' amplitudes and the classification result, these parameters are stored into the database of the vector layer.

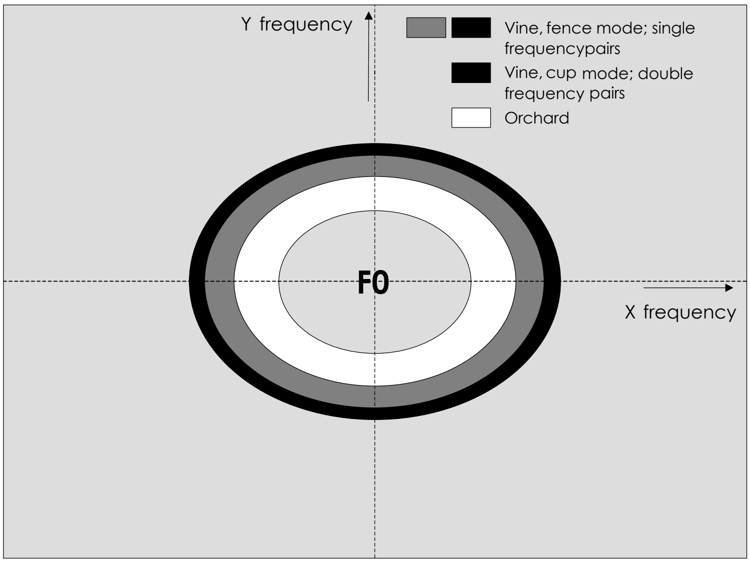

Figure 2 Circularly constant frequency sections within which the peaks of the corresponding classes need to be located.

6. RESULTS AND DISCUSSION

An interesting test scene was extracted from the image mosaic (figure 3). It does not represent an average 'normal' situation, but shows the complexity of the vineyard environment by a number of 'unconventional', extremely varied field patterns, thereby testifying for the need of a robust method. We will illustrate how the procedure works on field 1 (figure 4), which is a non weeded goblet field with grass growing in discontinuous patches and in-between a strongly contrasted crusted soil surface. We observe that our method is not disturbed by this heterogeneity (figure 4).
Although robust with respect to within-field variations, the method is not entirely insensitive with respect to the quantity of information provided, i.e. the size of the extracted field segment. A few fields have been left out. Some very small fields appeared too small after buffering (no. 4, 12, 25, 29). It was empirically estimated that a threshold buffered size of about 800 m^2 was needed. Another artefact results from more or less diagonally oriented buffered fields with a very small width (no. 28, 42). There is not enough data and the edge effect imposes a perpendicular frequency peak leading to a false 'wire-trained' classification. In this case a co-occurrence analysis with shift in the direction of this frequency could have overcome this problem.

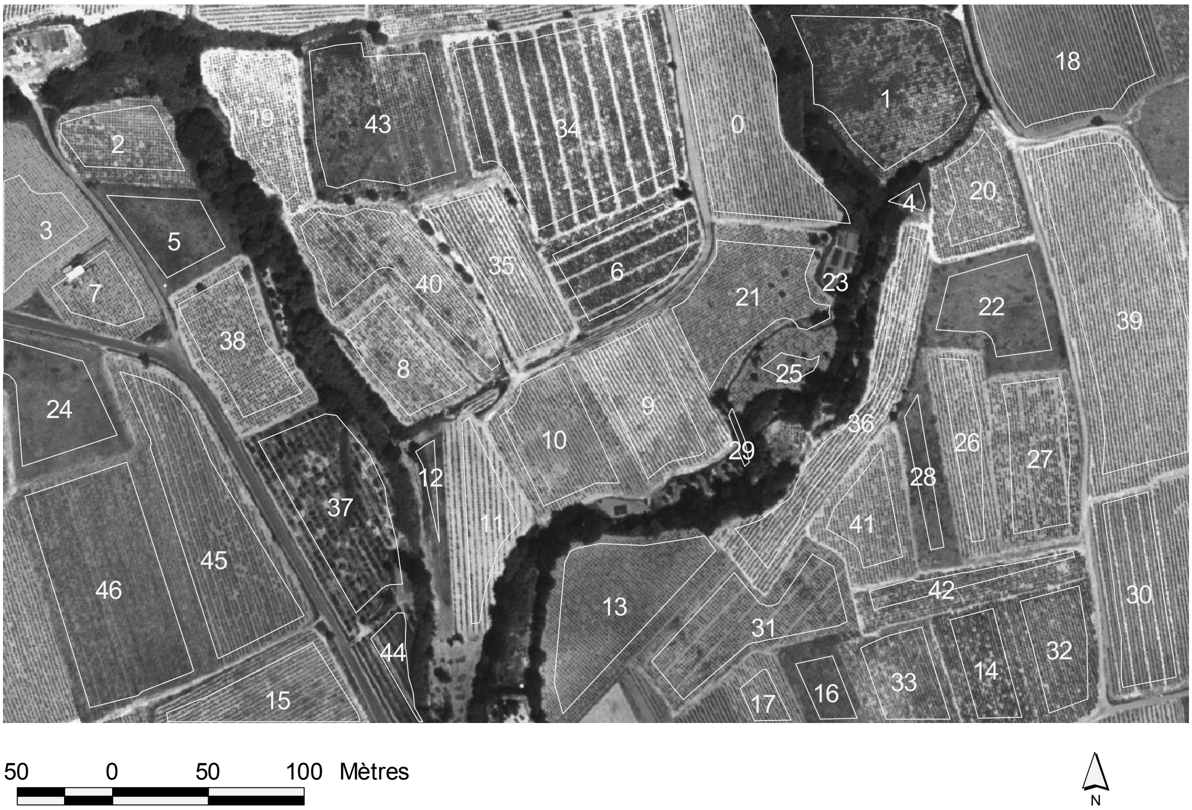

Figure 3 Extract of an image mosaic covering an area situated in the La Peyne valley. The images were taken at the end of may 1998.

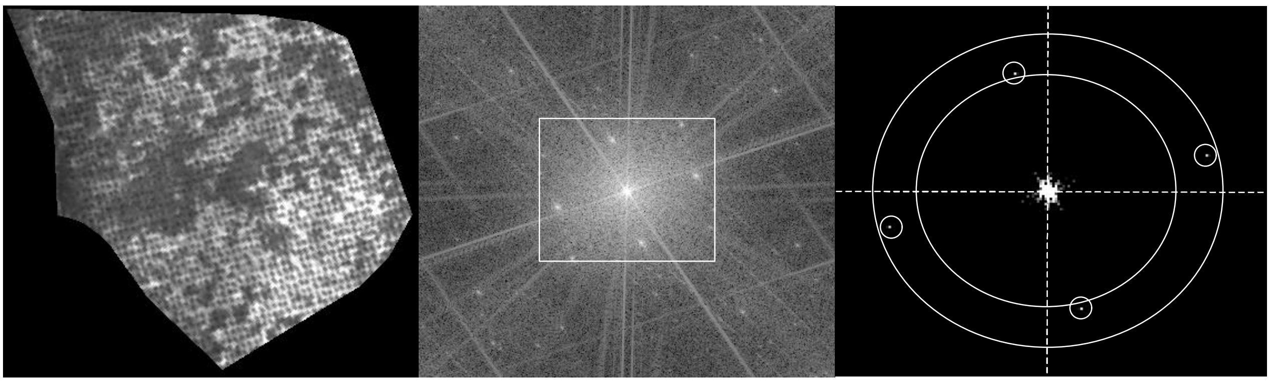

Figure 4 Illustration of the procedure on field 1 (figure 3). Left shows the image information extracted and temporarily stored in a square matrix; the centre shows the Fourier transform of this image; right shows the frequencies remaining after thresholding (only the part contained within the white rectangle of the centre image is represented, because outside no frequencies remained). Both pixel pairs, visible within the small white circles, are located within the vine frequency zone. The pairs are, once transformed into geographical space, near perpendicular. These observations lead to classification as goblet mode. From their position with respect to the centre spacing and orientation are computed.

6.1 Training mode

The results of the application of the model to the example image of figure 3 show that the number of erroneous classifications is small (5 out of 41). Moreover, these classification errors (no. 10, 11, 14, 27, 33) provide a very interesting information. All are cases which departed from our taxonomy. Fields no. 10 and 11 are actually in goblet mode, because they are self supporting (no metal wires), but their planting pattern is very unorthodox, with a strong line structure. Fields no. 14 and 33 do have a typical goblet geometry, but the amplitude of the perpendicular (to the main direction) peak is too weak for the field to be recognised as goblet-trained. This is due to the unique, preferential

ploughing direction leading to the occurrence of a small ridge with grasses between plants similarly to wire-trained fields. Finally, field no. 27 is erroneously classified as goblet, because the extensively managed field has a high number of gaps, e.g. the spatially discrete character of the crop has been recognised, but lines are too discontinuous for the field to be recognised as goblet mode.
The lesson to be learned is that the amplitude of the frequency peaks and the difference between the amplitudes of the perpendicular peak pairs provide an important information on the degree of 'getting into line' of intermediate cases, which is hidden by the simple field observations. This has been verified by additional field observations that confirm the model's indication for 18 out of 20 goblet fields.
Apart from these remarks the method works well on an important variety of situations: fallow fields, orchards with a partially grass covered soil surface, dark and bright vineyards due to soil surface type, or to view angle variation in the image mosaic, vineyards with a discontinuous soil surface signal, and even on fields where the spatial structure is split up in blocks (no. 6, 30, 31, 34).

6.2 Spacing

We showed previously that the training mode does not always comply with the generally advised and traditionally used spacing described in paragraph 2.2. This is why it is important to determine spacing independent from the training mode. However, ten of the eleven wire-trained fields indeed have a row spacing between 2.0 and 2.5m (no. 46 being a goblet field put on wire fences), and all 17 goblet fields have a traditional near square spacing.
The method allows for a very accurate estimation. This can be seen from the example in figure 4: the pixel corresponding to the frequency peak is unambiguously identified, so the estimation error is less or equal to the pixel size. This within-pixel variation is more important at low frequencies, where pixels contain a higher range of frequencies. This variation is less than 2% in the vineyard frequency sector and grows up to 5% in the orchard frequency sector. This theory is confirmed by precise on-screen measurements on a set of 20 randomly chosen goblet and wire-trained vineyards. These measurements, realised in the two planting directions over the whole field, were considered to be more precise than field measurements. They resulted in an absolute average difference of 1.6 cm, i.e. about 1%, with respect to the model's results on these fields.

6.3 Orientation

The orientation of rows and grid patterns measured directly on the image mosaic, using a subsample of 20 fields, is in very good agreement with that estimated by our procedure. An average absolute difference of 1.2 degrees was found, which is within the accuracy range of direct measurements. Precise field measurements were made on this selection of fields using a land surveyor's compass. The average absolute difference between model results and field measurements is 1.3 degrees, i.e. less than 1% error, with 20 out of 30 measurements having a deviation of 1 degree or less. Although weak, the average absolute difference between the image mosaic and field measurements of 0.7 degrees shows that part of this error may be induced by the warping of the images.

7. CONCLUSION

A method is proposed for automatic identification of vineyards and their training mode on a per-field basis. It also provides a description of the spatial crop structure. The method developed was demonstrated to be very robust, allowing to extract accurately quantitative variables, handling the complex and variable radiometry of the environment considered. Moreover the model can be transposed to other regions characterised by other crops or frequencies by a simple adjustment of criteria. The computational efficiency of the procedure and the fact that results are directly available for use in spatial analysis without creating an intermediate or additional image layer makes this method well suited for operational use. The model could even be incorporated in a GIS, thereby avoiding early 'binding', i.e. linking semantically the results of a scene interpretation to geographic features, as proposed by Gahegan and Flack (1996) . The output format could be user-defined, thereby putting off the task of choosing a description until the current user task is known.
Apart from a few artefacts, all fields are correctly classified. However, ambiguities occur obviously for training modes intermediate between 'goblet' and 'wire-trained' classes. It can be argued that in this case and in the context of environmental studies the information provided by the method developed is more valuable than the information resulting from field observations. Apart from a 'boolean' classification, the degree of lining as expressed by the frequency amplitudes can be very useful.
A general condition is that part of the sun-lit soil surface between the vines or vine rows has to be present in the image segment corresponding to a field. The restriction this imposes on the spatial resolution has been discussed, but the geometrical conditions also have to allow for the soil surface to be "seen" by the sensor. It has to be verified that the combined action of viewing angle, slope, orientation, plant height and sun elevation satisfy this condition throughout the image. Care should be taken with the interpretation of results from very narrow buffered fields and a minimum size

threshold is required, below which a buffered field cannot be analysed. Lastly, to be able to use the exact quantitative variables as physical parameters, the image warping method needs to be of a comparable high quality.

8. PERSPECTIVES

The model developed is applied to data sets of the study area and provides information that will constitute input parameters for a spatially distributed semi-empirical hydrological model under construction at the INRA, Montpellier. The model results also allow us to proceed to an in-depth per-field vineyard soil surface analysis. For each field identified as vineyard, a robust procedure allows the sun-lit soil surface to be extracted by a multi-scale median transform, allowing to recognise the object, which then is adjusted to its width by per-field erosion/dilation. Knowing the geometric conditions of viewing and illumination, the crop cover can be calculated. A final phase concerns the assessment of the surface conditions through the soil surface signal.

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