

## EXTRACTION OF VINEYARDS OUT OF AERIAL ORTHO-IMAGE USING TEXTURE INFORMATION

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### ABSTRACT:

A cartography of vineyards is required by many mapping agencies, both to draw topographic maps and to complete the “vineyard” layer of large scale land cover databases. In this paper, two distinct approaches are proposed and tested to achieve a (semi-)automatic detection of vineyards task out of 50cm ground resolution ortho-images. Both are object based approaches relying on image texture analysis in homogeneous land cover regions. Therefore, the first step (common to both approaches) is a segmentation of the image into homogeneous land cover regions. These regions can then be classified as vineyards or not by the next approaches.

A first approach consists in a frequency analysis of the image texture in each region. A semi-variogram is first calculated from the ortho-image for each region of the segmentation. A Fourier transform (FFT) of this semi-variogram of the image is then considered. If a periodic signal with a high frequency (i.e. of which the frequency is upper than a threshold) is identified, the region is labelled as a vineyard.

The second approach is a supervised (per region) land cover classification one. It uses texture indexes calculated from ortho-images as input image information. In particular, some texture indexes derived from SIFT descriptors calculated from ortho-images have been used in the experiments, giving good results.

## 1 INTRODUCTION

### 1.1 Context

The French national mapping agency (IGN) is responsible for the production of several national geographic databases (including many topographic classes such as buildings, roads, forests, water system, cadastral parcels, ...) covering the whole French territory. It also has to produce the national base map. Huge efforts have been made during the last decade to derive this map (almost completely) automatically from these digital databases. Nevertheless some items still miss in the databases or exist but have not been updated for quite a long time, whereas they are necessary for the map to be drawn. For instance, the legend of the national base map includes a vineyard item, whereas this class is not completely up-to-date on the whole territory. This updating task is indeed quite long and performed manually by operators, while this legend item is not considered among the most important for the quality of the map.

Furthermore, during forecoming years, a new national large scale land cover database will have to be plotted by IGN. The nomenclature of this new database will also include a “vineyard” layer. Thus, in the future, the vineyards objects of the maps will be directly drawn from this database.

As a consequence, there is a growing need for a new cartography of vineyards, and therefore for a new process to be able to produce it and then to update it.

### 1.2 Existing databases

However, several databases concerning vineyards produced by other authorities are already available. Such external sources could thus be used to help to produce the “vineyards” layer of the future land cover database.

Nevertheless, all of them are different from what is required :

- On one hand, some of these databases are very exhaustive (in the sense that almost all cadastral parcels containing a vineyard part are present) but only mention the value of the area covered by vineyards per cadastral parcel. In these databases, vineyards are not precisely delineated among the parcels, as shown by fig. 1.
- On the other hand, other ones offer locally a very fine plotting of vineyards but are not exhaustive at all.

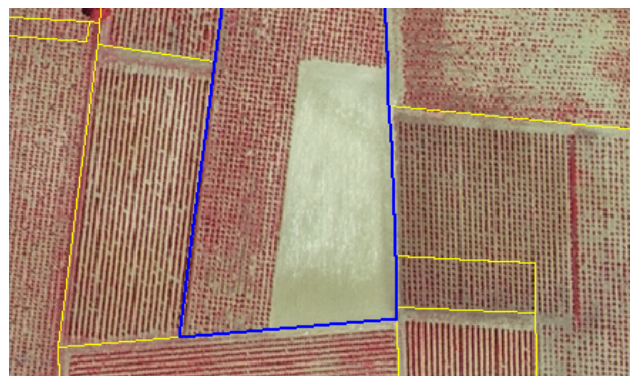


Figure 1: As in the blue parcel, vineyard objects are not precisely delineated in this database, although it is very exhaustive.

As a consequence, the required vineyard layer can not be automatically derived directly owing to a simple integration of these data sources (even for the most exhaustive among them). Therefore, vineyards will sometimes have to be extracted (at least manually and selectively to correct some mistakes) directly from aerial ortho-images to produce the “vineyard” layer of the national land cover database. Such a task should therefore be (at least partially) automated.

Furthermore, it would also be interesting to be able to qualify the

available external data sources. A possible way to achieve this can consist in comparing them to the result of an automatic detection of vineyards from aerial image data, or simply analysing indexes used by this detection method. Database parcels identified as “not sure” would then be checked by operators.

Besides, some vineyard parcels can be missed even in the most exhaustive information sources and would be interesting to be detected (semi-)automatically out of aerial images.

As a consequence, there is a growing need for semi-automatic tools to detect vineyards out of aerial images.

Images used for this task would be 4 bands (red, green, blue and near infrared bands) 50cm ground resolution ortho-images of the national ortho-image database of IGN.

### 1.3 Difficulties

Several difficulties are encountered for this vineyard detection.

**1.3.1 A varying appearance** Vineyards can have a very different appearance from one parcel to another, as it can be seen on figure 2. This depends on various parameters, such as the age of the plants or the existence of several cultural methods :

- Vineyards have a more or less grassy ground : some of them have a bare ground, whereas other ones are covered by grass. Besides, this can vary inside a same parcel, probably depending on the quality and the moisture of the ground.
- The vineyard texture can be more or less pronounced, depending on the size (and the age) of the plants, and the fact they have more or less leaves.
- Some vineyards are cultivated by rows, whereas in other ones, vine plants are isolated. As a consequence, the texture of these parcels varies from clearly linear to dotted, as on the second picture of figure 2.
- Other vineyards parcels consists in a succession of bands of grass and groups of rows of vine plants, presenting thus a “bar code” texture, as on the first picture of figure 2.

To sum it up, vineyards have a very varying appearance and pure radiometric information is not sufficient to discriminate them from other classes. However, in all cases, vineyards always have a **high frequency periodic (quite linear) repetitive texture**.

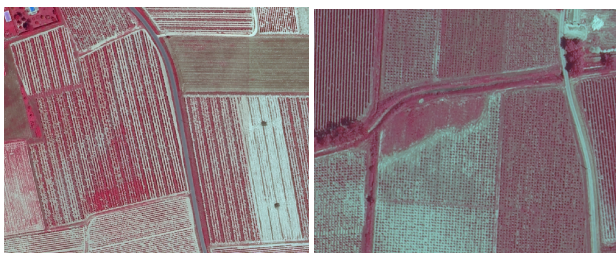


Figure 2: The appearance of vineyards varies.

**1.3.2 Other periodic textured objects** Nevertheless, vineyard is not the only land cover class with an almost repetitive structure. Other kinds of land cover can have a quite similar texture, leading to possible misclassifications.

**Orchards** also have a periodic (sometimes linear) texture but most of the time it has slightly lower frequency. (Inter-row spacing is more important and plants are larger.) Nevertheless, this also depends on cultural practises. There are even mixed vineyard/orchard parcels alternating rows of vine plants and rows of fruit trees.

**Tilled fields** (and especially recently plowed ones) have also often a high frequency linear quite periodic texture, sometimes locally quite similar to the one of vineyards, but less pronounced. This will be an important cause of misclassification, especially on images captured in early spring, when vine plants are not fully grown and fields have just been tilled. Nevertheless, knowledge from external databases of section 1.2 could be an help to prevent them, some parcels being clearly identified as non vineyards ones.

### 1.4 Methodology

**1.4.1 State-of-the-art** The extraction of vineyards out of aerial or very high resolution satellite has been widely studied, and several approaches have already been proposed.

Some approaches are based on Fourier transform. For instance, in (Delenne et al., 2008) a Fourier transform of image parts is first computed. The peaks corresponding to vineyard parcels are then extracted in the Fourier space among the frequencies corresponding to suitable row spacing for this land cover class. Each detected peak is then modelled by a Gabor function and the image is convolved by this Gabor filter, revealing the corresponding vineyard as the part of the image having a strong answer (up to a threshold) to the filter. This method is interesting since it requires no previous segmentation of the image. In (Chanussot et al., 2005), some parameters (inter-row spacing, holes ...) are estimated from a Radon transform of the Fourier transform of crops of the image corresponding to vine parcels, but the context is different from the one in this paper since detecting vineyards is not aimed at there and work is performed on higher resolution aerial images.

Other approaches are object ones (thus requiring a previous segmentation of the image) using semi-variograms. For instance, (Trias-Sanz, 2006b) first calculates the semi-variogram of each cadastral parcel, and then uses this information to estimate whether they have a periodic structure, and whether they correspond to vineyard or other land cover classes. (Balaguer et al., 2010) calculates the semi-variogram of each cadastral parcels and derives a set of features from it. These features are then used in a supervised classification process.

Several approaches are based on classification using textural features. For instance, Haralick and morphological features are used to detect orchards in (Kupidura and Gwadera, 2010). A bank of Gabor filters can also be used.

Bag-of-words approaches used in (Lienou et al., 2010) to semantize lower resolution satellite images could also be used.

**1.4.2 Proposed approaches** In this paper, two distinct approaches have been proposed and tested to achieve this semi-automatic detection of vineyards out of 50 cm ground resolution ortho-images from the national ortho-image database. Both are object based approaches relying on image texture analysis in homogeneous land cover regions. Therefore, the first step (common to both approaches) is a segmentation of the image into homogeneous land cover regions (and even more into regions having a homogeneous image texture). These regions can then be labelled as vineyards or not by the following approaches.

The first approach consists in a frequency analysis of the image texture in each region. A semi-variogram is first calculated from ortho-image for each region of the segmentation. A Fourier transform (FFT) of this semi-variogram of the image is then considered. If a periodic signal with a high frequency (i.e. of which the frequency is upper than a threshold) is identified, the region is labelled as a vineyard.

The second approach is a supervised (per region) land cover classification one. It uses texture indexes calculated from ortho-images as input image information. In particular, some texture indexes derived from SIFT descriptors calculated from ortho-images have been used in the experiments, giving good results.

To sum it, the proposed process consists in the next steps :

1. **Segment** the ortho-image into homogeneous regions
2. **Detect** vineyards regions using both proposed approaches
3. (Optional : **Merge** results obtained by these two approaches)
4. (Optional : **Post-process** (delete too small regions, intersect with parcel identified as containing vineyards in existing databases, clean classification using other databases (roads, buildings, forest,...), simplify contours of detected objects ...))

## 2 SEGMENTATION

As both proposed approaches to detect vineyards from aerial images are object based ones, the images have first to be segmented into homogeneous land cover regions (and even more into regions having a homogeneous image texture). The cadastral parcels can not be used directly as a segmentation because they can contain several distinct land cover classes. Therefore, this task is performed directly from image information using image segmentation algorithms.

This is here achieved thanks to the multi-scale segmentation described in (Guigues et al., 2006). A pyramid of segmentations of the image is first computed from a watershed over segmentation. Each level of this pyramid corresponds to an alternative between detail and generalization. This pyramid is then cut at a level chosen to obtain a suitable image partition. This cut level is empirically selected by the user by visual inspection on a small part of the data set area. It is a compromise between desired details and the size of regions which is not easy to set in the present context since on one hand, if this image is over segmented, some regions will be too small to have meaning and are at risk to be misclassified. Besides, on vineyard parcels, there is a risk to obtain one region per row of vine plants and one region per inter-row, making it impossible to extract vineyard by texture analysis of the regions. On the other hand, some regions of a too coarse segmentation include several distinct land cover classes. Furthermore, in the present case, it is even important to prevent to have regions containing only vineyards but with different texture parameters (orientation, "density"), making it difficult to extract vineyards by simply analysing these regions (e.g. on figure 3).

From a more operational point of view, a way to correct this possible problem of too coarse segmentation could consist in using the cadastral parcels at the end of the segmentation process, to divide segmentation regions belonging to several parcels. Too small regions created by this operation are then merged to their neighbour with the longest common border.

In these experiments, segmentation has directly been processed on red-green-blue images.

## 3 FIRST APPROACH : "FREQUENCY ANALYSIS"

### 3.1 Definitions

**Semi-variogram** Let  $I$  be a  $n$  band image and let  $R$  be a region of the segmentation of  $I$ .

An interesting information is the "mean" variation of the radiometry of the image for a 2D shift  $(a, b)$  inside the region  $R$ . This value is obtained applying the next formula :

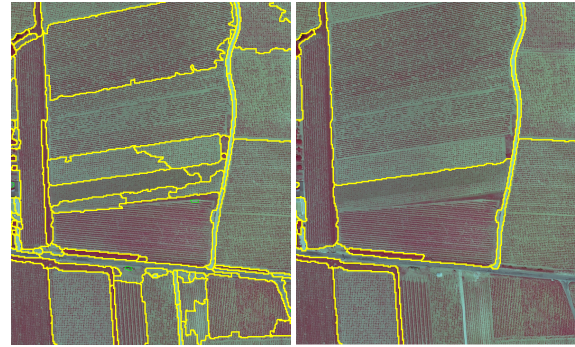


Figure 3: From left to right : example of a suitable and of a too coarse segmentation.

$$V_R(a, b) = \frac{1}{\#R} \sum_{(x,y) \in R; (x+a, y+b) \in R} \|I(x, y) - I(x+a, y+b)\|$$

The function  $V_R$  is called the **semi-variogram** of the image  $I$  inside the region  $R$ . (Clark, 1979)

**Fourier transform** Let  $f$  be a 2D function and let  $F$  be the Fourier transform of  $f$  :  $F = \mathcal{TF}(f)$  (Fourier, 1822) :

$$F(u, v) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(x, y) e^{-2\pi i(ux+vy)} \cdot dx \cdot dy$$

The Fourier transform is a common tool to study the frequency and the behaviour of a periodic signal. Concerning implementation, Fast Fourier Transform (FFT) algorithms of the FFTW library (FFTW, last visited on the 16th of January 2012) have been used in this study.

### 3.2 Proposed approach

The proposed method for vineyard detection consists of the following steps :

1. **Segment** the image into (almost) homogeneous texture regions. (cf part 2)
2. **Compute a vineyard index** for each region  $R$ 
  - (a) Calculate the semi-variogram  $V_R$  of the red band of the image in region  $R$
  - (b) Calculate the FFT  $\mathcal{TF}(V_R)$  of this semi-variogram
  - (c) Analyse the modulus of  $\mathcal{TF}(V_R)$  : if a peak exists for a frequency higher than a certain threshold, it corresponds to a vineyard area. This is used to define a "vineyard index", as explained below.
3. **Detect vineyards by simply thresholding the "vineyard" index** previously obtained.

**A "vineyard index" :** Analysing the modulus of the Fourier transform of the semi-variogram of a region makes it possible to decide whether it is a vineyard area. It is also a way to identify the direction and the wave length (i.e. the inter-row spacing) of its oriented texture.

Let  $\mathcal{TF}(V_R)$  be the Fourier transform of the variogram  $V_R$  of the image inside region  $R$ . To detect only vineyards, only the existence of a peak in  $|\mathcal{TF}(V_R)|$  among frequencies corresponding to possible "vineyards" wave length (i.e. row spacing) is checked. As  $|\mathcal{TF}(V_R)|$  is maximum in  $(0; 0)$ , its second maximum is sought, i.e.  $(\hat{u}; \hat{v}) = \operatorname{argmax}_{(u,v) \neq (0,0)} |\mathcal{TF}(V_R)|$ .

The distance between  $(\hat{u}; \hat{v})$  and  $(0; 0)$  is then calculated : this value  $\sqrt{\hat{u}^2 + \hat{v}^2}$  is the "vineyard index" previously mentioned making it possible to discriminate between vineyards and other classes. Thus, a too low value means either that the region has no repetitive and directional texture or that it has such a texture but for a too low frequency to be a vineyard. Some examples of this per region index are shown on fig. 4 and some examples of this per region analysis scheme are shown by fig. 8 for different land cover classes.

**Comments :** Compared to other approaches based on Fourier transform, using the semi-variogram as an intermediate step is a way to use the information of the whole region whatever its shape. On the other hand, contrary to (Trias-Sanz, 2006b, Balaguer et al., 2010) who also use semi-variograms but try to classify several classes, only vineyards are sought in this study. As a consequence, a more simple analysis simply using the Fourier transform is possible (to detect high frequency periodic texture).

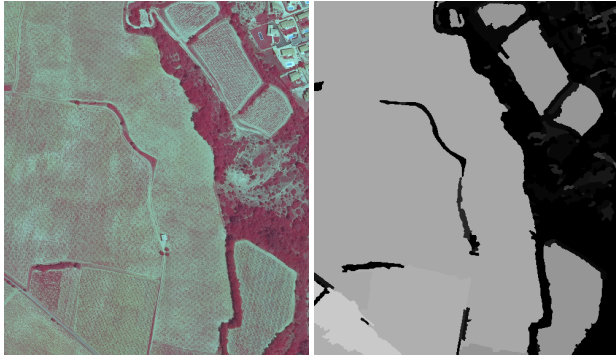


Figure 4: “Vineyard” index computed from the left image.

#### 4 SECOND APPROACH : CLASSIFICATION USING TEXTURAL FEATURES

The second approach consists in performing a per region classification of the image using an association of texture channels.

##### 4.1 SIFT based features

SIFT based texture features have been tested, instead of well known image texture features such as Gabor filters and Haralick indexes.

SIFT (*Scale Invariant Feature Transform*) described with details in (Lowe, 2004) is both a multiscale keypoints detector (also known as DoG) and a keypoint descriptor used for point matching purposes. The SIFT descriptor describes the behaviour of the image in the neighbourhood of its associated keypoint. Thus, it is also a texture descriptor, which has already been used for remote sensing classification tasks such as in (Yang and Newsam, 2008). The standard SIFT scheme is described below :

1. Multiscale keypoints are detected in images.
2. An orientation is computed and assigned to each detected keypoint. (It corresponds to the main direction of pixel gradients in the neighbourhood of the keypoint).
3. A SIFT descriptor (relative to the orientation and scale of the keypoint) is then calculated for each detected keypoint.

Contrary to the standard SIFT pipeline presented above, descriptors are here calculated for a regular grid of points (i.e. the detector part is not used) at the image resolution (the multiscale aspect of SIFT is not used), since the interesting information for the present application is at the lowest level of the scale space.

SIFT descriptors are 128 dimensional vectors. This is quite important and it is useful to reduce their dimensionality for the classification task. Two strategies are possible to achieve this :

- A possible way is a bag-of-words one.  $N$  words are extracted (by clustering) from the set of all keypoints, and distances to these words are then studied.

- An other solution consists in performing a principal component analysis (PCA) of a set of SIFT descriptors. Only the first  $N$  components are kept.

This second solution has been used here. Only the three first components of the PCA of SIFT descriptors are kept providing (after rasterization) images such as the one shown by figure 5. Experiments have then showed that the best classification results have been obtained using the second and the third of these channels.

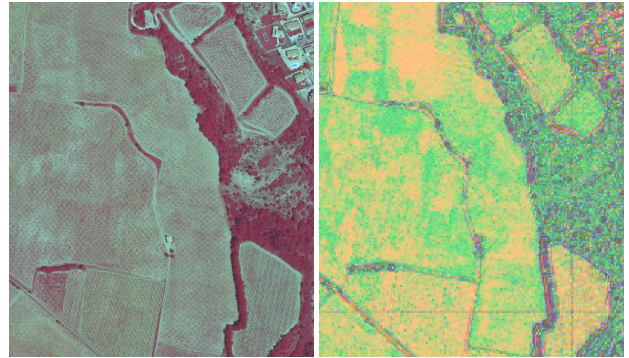


Figure 5: The second image is a texture image obtained from SIFT descriptors extracted from the left image.

##### 4.2 Classification algorithm

The regions of the segmentation are classified by the **per region** classification algorithms described in (Trias-Sanz, 2006a). This tool works in two steps :

**1 - Model estimation** from training data captured by an operator : first, for each class, the best parameters of several statistical distributions (such as Gaussian, laplacian laws but also histograms (raw or obtained by kernel density estimation)...) are computed to fit to the radiometric  $n$ -dimensional histogram of the class (with  $n$  number of image derived channels used for the classification). Then the best model is selected thanks to a Bayes Information Criterion enabling to choose an alternative between fit to data and model complexity.

**2 - Classification** : The image can then be classified according to the previously estimated statistical model of the radiometry of the different classes. Several per pixel and per region classification algorithms are proposed in (Trias-Sanz, 2006a) :

**Maximum A Posteriori (MAP) and Maximum Likelihood (ML) per region classification algorithms** : The label  $c_o(R)$  given to a region  $R$  is its most probable class according to the model previously estimated (and to prior probabilities). Hence, with the ML algorithm,  $c_o(R)$  is the class  $c$  that maximizes the following

function : 
$$\left( \prod_{pixel\ s \in R} P_{model}(I(s)|c(s) = c) \right)^{\frac{1}{Card\ R}}$$
 with  $I(s)$  standing for the radiometry vector of pixel  $s$ ,  $c(z)$  meaning region or pixel “ $z$ ’s class” and  $P(c(z) = c)$  standing for the probability for pixel or region  $z$  to belong to class  $c$ .

**Per region classification algorithms based on the comparison of distributions** : The label given to a region is the class with the most similar model to the distribution of pixel values in the region to be classified. The  $\chi^2$  statistic and the Kullback-Leibler divergence (also called relative entropy) are two possible dissimilarity coefficients that can be used to compare these distributions.

During experiments, these different classification algorithms have been tested, giving almost the same results.

## 5 MERGE RESULTS

Results provided by the two approaches can be merged using the next strategy. First, intersection and union masks of objects detected by both approaches are computed. Secondly, too small elements of the intersection mask are deleted. Lastly, objects of the union mask are deleted if they don't contain an object of the intersection mask. Remaining objects of this cleaned union mask are the final objects.

## 6 EXPERIMENTS AND RESULTS

The method has been tested on 2 datasets. Both consist of aerial 50 cm ground resolution ortho-images. Groundtruth data is not the same.

### 6.1 First data set

On this 242 km<sup>2</sup> test area, images have been captured during summer time.

Results of the vineyard extraction processes have been compared to a groundtruth derived from cadastral parcels labelled by an operator into the following classes :

- more than 90% of the parcel covered by vineyard
- from 50% to 90% of the parcel covered by vineyard
- from 10% to 50% of the parcel covered by vineyard
- less than 10% of the parcel covered by vineyard
- no vineyard on the parcel

“Confusion matrices” (see table 1) have then been calculated.

For both methods, the percentage of detected vineyard among the different categories of labelled parcels is coherent to what could be expected. The vineyards are globally retrieved (see fig. 7). Nevertheless, some parcels have been forgotten (especially the ones with a “bar code” texture previously mentioned). On the opposite, some orchards or tilled field areas have also been detected as vineyards.

Most of the time, detected vineyard areas have a more precise delineation than the cadastral parcel. However, their border can also sometimes be irregular.

### 6.2 Second data set

This second data set covers a 400 km<sup>2</sup> and includes a true for evaluation, since vine areas have already been plotted by an operator there.

Nevertheless, aerial images have been captured in early spring and vegetation was not fully grown (as on fig. 6), making it difficult in some parts to see rows of vine plants. Besides, many fields have also just been tilled. As a consequence, vineyards are often difficult to discriminate from these other classes (even for a human being) leading to many misclassifications. Therefore, obtained results are not so good than for the previous data set.

63% of the groundtruth vine area is detected by the “frequency analysis” method, but 42% of the area of detected vineyards is over-detection.

75% of the groundtruth vine area is detected by the “classification” approach (using the ML algorithm), but 39% of the area of detected vineyards is over-detection.

Merging these results leads to an improvement since 75% of vineyard area is detected and over-detection only concerns 35% of the detected vineyard area.

## 7 CONCLUSION

To sum it up, obtained results are not perfect (most of all for the second data set) but remain very encouraging, especially in

Table 1: First data set : results of the approaches “frequency analysis” and “classification” (using per region maximum likelihood classification algorithm applied to SIFT based texture indexes)

	vineyard	non vineyard	vineyard	non vineyard
groundtruth	First approach “frequency”		Second approach “classification”	
90% ≤ vineyard	87%	13%	80%	20%
50% ≤ vineyard < 90%	69%	31%	61%	39%
10% ≤ vineyard < 50%	41%	59%	33%	67%
0% < vineyard < 10%	12%	88%	9%	91%
non vineyard	1.5%		1%	



Figure 6: Second data set : example of vineyard where plants are not fully grown, making it difficult to be detected

this specific context where additional information (such as external databases concerning vineyards or other land cover items re available) could be used to prevent over-detection and to clean the detection results. (Such information has not been used in the previous experiments.) Work could now be done to :

- improve the first approach, to try to better discriminate vineyards from tilled fields, using a complementary index derived from the Fourier transform of the semi-variogram, to measure to what extent a texture is “pronounced”.
- merge the results, using directly confidence indexes given by the two approaches
- improve the quality of the border of detected vineyards (making them be less noisy), for instance using an approach similar to the one of (Delenne et al., 2008). From the previous frequency analysis, the best parameters for a Gabor function are estimated to describe the region identified as vineyard. The contour of this region could then be fit (using for instance an active contour model) to the result of the convolution of the image with this Gabor function.

## ACKNOWLEDGEMENTS

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## REFERENCES

Balaguer, A., Ruiz, L., Hermosilla, T. and Recio, J., 2010. Definition of a comprehensive set of texture semivariogram features and their evaluation for object-oriented image classification. *Computers & Geosciences* 36(2), pp. 231 – 240.



Figure 7: First data set : results of the approaches “frequency analysis” (top) and “classification” (bottom) using per region ML classification algorithm applied to SIFT based texture indexes

Chanussot, J., Bas, P. and Bombrun, L., 2005. Airborne remote sensing of vineyards for the detection of dead vine trees. In: Proc. of the IEEE International Geoscience And Remote Sensing Symposium (IGARSS’05), Seoul, Korea.

Clark, I., 1979. Practical Geostatistics. Elsevier applied science, London. UK.

Delenne, C., Rabatel, G. and Deshayes, M., 2008. An automated frequency analysis for vine plot detection and delineation in remote sensing. IEEE Geoscience and Remote Sensing Letters 5(3), pp. 341 – 345.

FFTW, last visited on the 16th of January 2012. Fastest Fourier Transform in the West (FFTW). <http://www.fftw.org/>.

Fourier, J., 1822. Théorie analytique de la chaleur. Firmin Didot, père et fils.

Guigues, L., Cocquerez, J.-P. and Le Men, H., 2006. Scale sets image analysis. International Journal of Computer Vision 68(3), pp. 289–317.

Kupidura, P. and Gwadera, L., 2010. Comparison of different approaches to extract heterogeneous objects from an image using an orchards example. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences 38 (Part 3B), pp. 13–18.

Lienou, M., Datcu, M. and Maître, H., 2010. Semantic annotation of satellite images using latent dirichlet allocation. IEEE Geoscience and Remote Sensing Letters 7(1), pp. 28 – 32.

Lowe, D. G., 2004. Distinctive image features from scale-invariant keypoints. International Journal of Computer Vision 60(2), pp. 91–110.

Trias-Sanz, R., 2006a. Semi-automatic high-resolution rural land cover classification. PhD thesis, Université Paris 5, Paris, France.

Trias-Sanz, R., 2006b. A texture orientation and period estimator for discriminating between forests, orchards, vineyards, and tilled fields. IEEE Transactions on Geoscience and Remote Sensing 44(10), pp. 2755–2760.

Yang, Y. and Newsam, S., 2008. Comparing SIFT descriptors and gabor texture features for classification of remote sensed imagery. In: Proc. of the 15th IEEE International Conference on Image Processing, San Diego, USA, pp. 1852–1855.

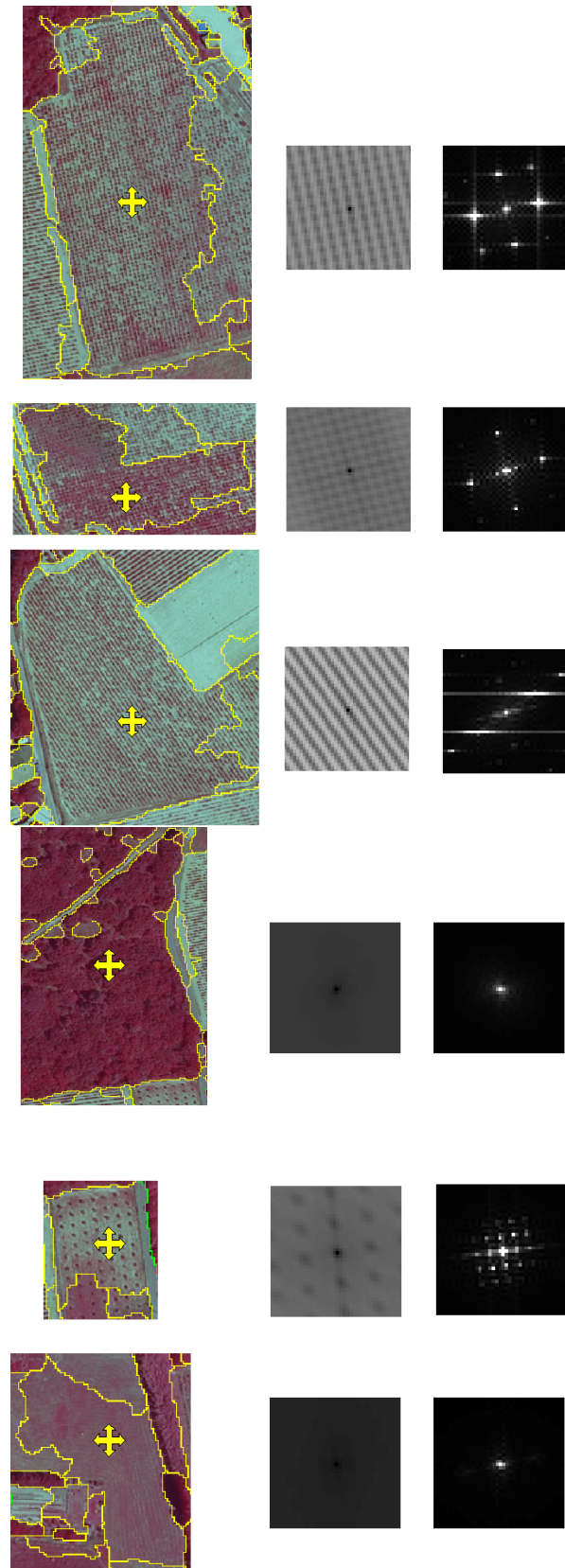


Figure 8: On each line, from left to right, segmented ortho-image, semi-variogram of the yellow crossed region, modulus of the FFT of this semi-variogram.