Classification and Information Extraction in Very High Resolution Satellite Images for Tree Crops Monitoring.

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ABSTRACT:
Recent access to Very High Spatial Resolution (VHSR) Satellite Images allows vegetation monitoring at metric and sub-metric scale, with individual trees now detectable. Therefore, it discloses new applications in precision agriculture for orchards and other tree crops.
In this paper, we present some methodological directions for classification, and extraction of specific agricultural information from these images. Aims are tree crop detection, plot mapping, species identification, and cropping-system characterization. This latter includes for instance row management (e.g. grid vs. line pattern, width of rows and inter-rows, row orientation), crown shape, and crown size estimation.
In this paper, we skip the segmentation step and consider that we have got a precise delimitation of plots that have a homogeneous content. To classify these plots, we have used expert knowledge in agronomy combined with image information in a decision tree.
Classification criteria were based on parameters resulting from the Fourier transform analysis or vegetation indices, derived as one single descriptor for the whole plot.
As a conclusion, the proposed methodology was found capable of classification and characterization of tree crops, provided the trees are clearly seen from above, and their planting is regular enough to give a response with Fourier analysis.

INTRODUCTION

This study is part of the ORFEO methodological program led by CNES (the French Space Agency) and several research institutes for the development of algorithms dedicated to image processing of the future Very High Spatial Resolution (VHSR) *Pléiades* sensor. This part of the project aims at developing automatic tools for the recognition of landscapes elements, such as groves and other tree plantations.

Since 2001 a new generation of satellite sensors delivers more accurate details and information of the Earth surface. We are now able to distinguish individual trees in VHSR satellite images. They should allow a better identification of the landscape units based on their content like, for the groves, the identification of the species or the crop system. Although current processing of this type of images goes back to airborne photographs and are based on visual photo-interpretation, this technique is time consuming and it is thus necessary to develop new tools based on computer processing for more automatic extraction of spatial information.

We propose to develop a multi-step VHSR-image processing sequence in an attempt to improve current practices in this field. The first step consists in a segmentation of the image in homogeneously textured units using tools previously published in the literature. The second step corresponds to an independent classification of the obtained units into a set of pre-defined classes; the segmentation preparing the best data set to be efficiently classified. The third step allows deriving some information about the grove structure and cropping practices.

In this paper, we present the second step of this treatment, based on an expert system grouping Fourier analysis, vegetation indexes comparison, and a decision tree. The objective is to classify each plot as a single unit, in a typology of height types of land use and structure.

1. MATERIAL

We focus in this study on a test-area in the South of France (Department of Gard), located south of Nîmes and north of St Gilles. It includes of a large variety of land use types, including several types of groves, orchards and forests. It thus gives the opportunity to test our method on a wide range of plot structures.

1.1 IMAGE DATA

We analyze a Quickbird [1] image acquired in July 2005 with a spatial resolution of 0.7 m in the panchromatic mode and 2.5 m in the multispectral mode (three spectral bands in the visible (blue, green and red) and near-infrared domains). These data were merged using a Brovey transform [2] to provide a multispectral image at 0.7 m spatial resolution, similar to that of the future *Pléiades* products. We finally extracted a subset of this image of 2411 pixels x 2122 pixels (2.5 km^2) to allow quick computing.

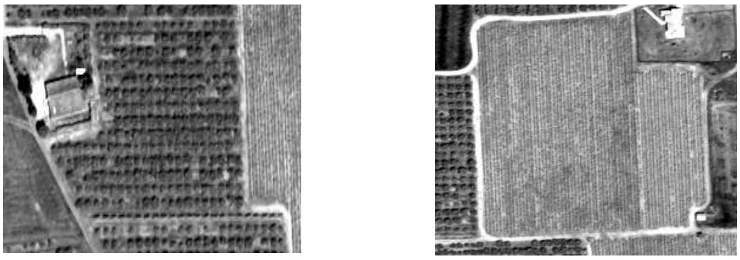

Figure 1: Test-image samples: peach grove (left) and vineyards (right).

Based on a field survey combined to photointerpretation, we produced a ground-truth image delineating and classifying each plot in a typology composed of height classes:

1. Fields (large crops in continuous cover: cereals, oilseeds…)
2. Market-garden (small crops in discontinuous cover: vegetables, strawberries…)
3. Vineyards
4. Young grid-groves (small trees with faint coverage density)
5. Adult grid-groves (big trees with dense cover)
6. Trellis-groves (row-structure of tree plantation due to wire-support)
7. Fallow lands with random isolated trees
8. Forests (natural tree canopy structure)

Inside this typology, we can observe that the Fields class (class 1) is the only one without any texture, while Fallow lands (class 7) and Forests (class 8) do not correspond to structured plantations. These three classes will thus be unprocessed when we will focus on the structured groves only.

Table 1: Number of plots in the ground-truth image for each class of interest

Class number	1	2	3	4	5	6	7	8
Number of plots	28	14	16	15	15	3	23	17

1.2 RESULT OF SEGMENTATION

Our choice of methodology is to classify each plot as a single object, assuming it has been already correctly segmented. Several algorithms can be used for this purpose [e.g. 3-4-5-6-7-8-9-10], that we won't detail here. We have though tested some of them, and evaluated their potential to provide plots of homogeneous land use systems with specific indicators of efficiency at the plot level of segmentation [11] and the operational point of view. As a result, we have finally applied the SxS hierachical segmentation [5-6] to extract image-subsets of each plot. The total number of individual subsets is 673, containing plots that correspond to one of the classes of interest, and others to untreated objects (roads, buildings, gardens, hedges, undefined landscape units…). Only the 131 plots related to classified ground-truth were processed for classification.

2. METHOD

The general principle of the proposed classification is based on a decision tree, including agronomical knowledge at each step of decision. Indeed, each different plot structure that can be observed is strongly correlated with the cropping practices for each kind of grove, often specific to the tree species (e.g.: vine, fruit, olive, pine…). This expert system is then fed by descriptors derived from the image processing, which give information about the structure (e.g. Fourier parameters, texture indices) or the density of the canopy (e.g. vegetation index). This section will first introduce and explain these descriptors, and then it will present the decision tree in its whole.

2.1 FOURIER PARAMETERS

Our approach is based on the Local Fast Fourier Transform [12]. We thus calculate the FFT on small windows that fit the inner area of each plot. The window size was fixed to 64 pixels, to reach enough repeatability of the planting structure and allows FFT. If the plot size is too small to contain such a window, its dimension is decreased to 32 pixels but the result will be of lower accuracy. To avoid singular sampling, at least three windows were used for each plot. The FFT is then derived for each of the different spectral bands of the multispectral image, and the final FFT spectrum is the result of the cumulative spectrum over these different bands. Finally, the Fourier spectrum for the whole plot is the mean of the spectrum derived for these three windows.

FFT spectrum of periodic features is characterized by the presence of peaks of strong intensity that give information about the corresponding image structure (cf. *Figure 2*). Indeed, if there is no peak, there is no periodic structure and the plot belongs to one of the classes "Fields", "Fallow lands" or "forests". If there are one to two peaks, the structure is linear. If there are four or more peaks, the structure is a grid arrangement of individual objects. First step of the analysis is thus to detect the exact number of peaks in the Fourier spectrum of each plot and classify it in the three main classes characterizing plot pattern: "rows", "grid", or "unstructured", this latter corresponding to the class untreated by the next steps. The expert knowledge is here important to discriminate between the different possible crops in each class. For instance, vineyards and orchards have different width or rows and inter-rows. Moreover, vine-stocks are fixed on wires and pruned to fit only one meter width, thus displayed as only one pixel line in the image. It is thus represented in the Fourier space by one single peak corresponding to the inter-row of about 2m [13]. Besides, trellis-orchards, like apple crops, can have a canopy width of two meters or more, thus displayed by a strip of several pixels in the image, and represented in the Fourier space by two different peaks corresponding respectively to the tree-row and the inter-row.

The FFT pattern of these two classes "rows" and "grid" is also characterized by the angle separating two different peaks: for linear structures, like vineyards or trellis-groves, the angle between the two principal peaks is null, while it is close to 90° for simple grid-groves or to 45° for complex grid-groves (cf. *Figure 2*).

In any case, the distance from one given peak to the centre of Fourier spectrum corresponds to the period of the structure, and to the width of the plantation pattern: rows or inter-rows for trellis-grove, and grid dimensions for grid-groves (cf. Table 2).

Finally, the association of these different observations on the Fourier patterns with expert knowledge allows an easy discrimination of the unstructured and the structured plots, and, in this latter case, plot classification in one of the four following classes: grid-grove, trellis-grove, vineyard, and market-garden.

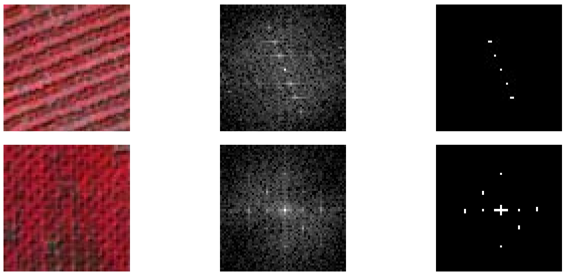

Figure 2: Fourier Transform of groves planted in trellis (top) and in grid (bottom)

Table 2: Relationships between Fourier parameters and class characteristics:

	Peaks	Angle between peaks	Distance to center (Plantation period)
Vineyards	1	0°	2m
Trellis-groves	2	0°	4m
Market-garden	1 or 2	0°	0.5 to 1m
Grid-groves	4 to 6	45 or 90°	6-8m

2.2 TEXTURAL INDICES

Textural indices based on the cooccurrence matrix derivation [13] can be particularly useful for discriminating plots of Fields, Fallow lands and Forests [14-15-16]. As an example, the Entropy index (cf. *Figure 3*) displays values close to zero for large fields, and different kinds of grey for the plots containing trees. Nevertheless, we have not analyzed in more detail this discrimination ability in the present study, which concerns mainly the managed groves, not the natural or fallow areas.

Figure 3: Panchromatic image (left) and Entropy index (right) of a subset of the studied image.

2.3 VEGETATION INDEX (NDVI)

The NDVI [17] is a vegetation index derived from multispectral images strongly correlated to the canopy biomass. It is thus efficient to distinguish different densities of groves having the same structure (cf. Figure 4). Indeed, the mean NDVI of a given plot will be higher if trees have a larger and denser crown. We will thus use this indicator to discriminate the young from the adult grid-groves. It can add some criteria for vineyard and other trellis-grove discrimination too. Finally, the NDVI also gives an indication of the canopy soil coverage; market-garden, which have very small covering ratios, will thus be easily distinguished from other row-crops (eg. vineyard, trellis-grove).

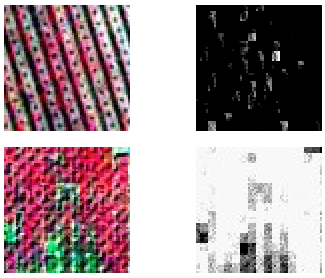

Figure 4: False colour composite image (left) and NDVI (right) of young (top) and adult (bottom) groves.

2.4 DECISION TREE

Based on the synthesis of these different observations on relevant descriptors of plot structure and content, we propose the following decision tree as the classification tool for the extracted plots (*Figure 5*).

1. The first analyzed parameter is the presence of peak in the Fourier spectrum. If there is no peak, the plot is not processed through the decision tree. It can possibly be treated afterwards with textural indexes-related classification if needed.
2. The angle between the different peaks in the Fourier pattern allows separating the plots in two groups, corresponding respectively to row and grid structures.
   a) In the case of grid-crops, the NDVI is used to determine the global age of the grove.
   b) In the case of row-crops, the number of peaks allows separating the plots as possible vineyards and possible trellis-grove, but still containing the market-gardens. Afterwards, the NDVI value helps extracting from these two groups the plots actually corresponding to market garden.

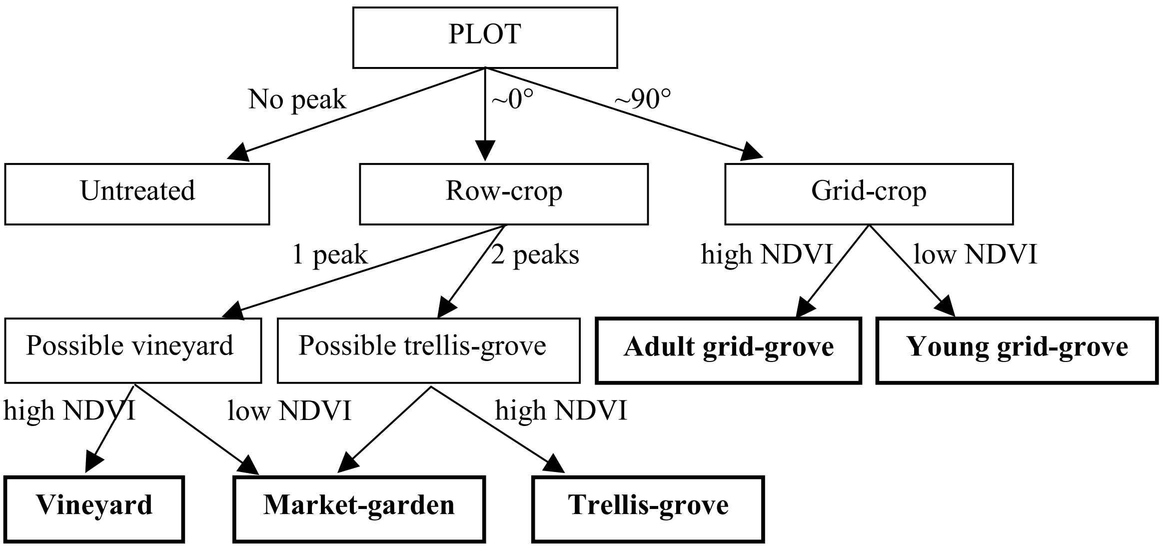

Figure 5: Sketch-map of the classifier decision tree.

Finally, we check that the planting period of the plots corresponds well to the specifications of the class it has been assigned to. If not, the plot is processed again with a lower filtering of the Fourier transform.

3. RESULTS AND DISCUSSION

Initially in this study, we wanted to distinguish height different classes. However, given the method based on the analysis of planting frequency, we cannot discriminate plots of Fields / Fallow lands / Forests at this stage. The confusion matrix of final classification of the 131 plots in the six resulting classes is given Table 1. At first sight, it shows that no big confusion is made between the large classes Row-crop and Grid-crop, and that the classification result is very good.

Even for adult grid-groves having a closed canopy, an FFT-peak can still be obtained, leading to good performances of the method.

However we can note that Market-gardens are poorly classified (only 64% of good occurrence). This class displays a great variability which may be due to confusion with vineyards. This occurs mainly after irrigation of the market-gardens which then display a high NDVI value similar to those of vineyards, and when vegetables cover a large row reaching vine-stock width.

About 14% error is committed on Fields, that are confused with vineyard or grove at an early development phase, when only partial vegetation cover does not hide completely the ploughing pattern in soil. When recently irrigated, they can even be mistaken with Market-gardens.

	Un-structured	Market-garden	Vineyards	Young grid-groves	Adult grid-groves	Trellis-groves
Fields	22	2	3	0	0	1
Fallow lands	23	0	0	0	0	0
Forests	17	0	0	0	0	0
Market-garden	2	9	2	1	0	0
Vineyards	0	2	14	0	0	0
Young grid-groves	1	2	0	10	2	0
Adult grid-groves	1	0	0	1	13	0
Trellis-groves	0	0	0	0	0	3

Table 3: Confusion Matrix

NDVI has also a limited effect for discriminating young-groves from adult ones when intercrops are not bare. Especially, 16% error is committed on the Young Grid-groves which understorey vegetation increases the total plot NDVI to value similar to those of adult-plots.

CONCLUSION AND PERSPECTIVES

As a conclusion, the method works well provided it uses lots of a priori knowledge on the study area. It allows discriminating between different tree crop structures and ages, with a good accuracy in most of the cases. Some classes would still need more efficient descriptors to be fully discriminated, and deeper analysis of NDVI, textural indices, and other descriptors will certainly improve the results.

Among perspectives of this study, it could be interesting to compare this classifier results with other methods relevant for processing complex data architectures, such as, for instance, the Support

Vector Machine [18]. It should also be more automatic to allow an operational use. Finally, it should be tested on several other types of groves to analyse its generic abilities.

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