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From pixel to vine parcel: a complete methodology for vineyard delineation and characterization using remote-sensing data

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Abstract

The increasing availability of Very High Spatial Resolution images enables accurate digital maps production as an aid for management in the agricultural domain. In this study we develop a comprehensive and automatic tool for vineyard detection, delineation and characterization using aerial images and without any parcel plan availability. In France, vineyard training methods in rows or grids generate periodic patterns which make frequency analysis a suitable approach. The proposed method computes a Fast Fourier Transform on an aerial image, providing the delineation of vineyards and the accurate evaluation of row orientation and interrow width. These characteristics are then used to extract individual vine rows, with the aim of detecting missing vine plants and characterizing cultural practices. Using the red channel of an aerial image, 90% of the parcels have been detected (56.2% with correct boundaries); 92% have been well classified according to their rate of missing vine plants and 81% according to their cultural practice (weed control method). The automatic process developed can be easily integrated into the final user's Geographical Information System and produces useful information for vineyard management.

Key words: Remote-sensing, precision viticulture, cultural practices, missing vine plants, segmentation.

1 Introduction

Since they provide precise and frequent large scale information, remote-sensing data can be used as an aid to decision-making. In winegrowing regions, accurate digital vineyards maps could be very useful to help the monitoring of quality compliance, especially for Controlled Origin Denomination areas,

31 where strict criteria are imposed, such as a rate of missing vine plants below
32 25%. The management of pollution, erosion and flood risks are other fields
33 that can take advantage of such maps as these risks depend on soil surface
34 conditions, which are directly linked to the kind of culture and cropping prac-
35 tice (see for example Lennartz et al. [1997] or Takken et al. [2001]). Distributed
36 hydrological models developed for cultivated catchments take into account the
37 spatial heterogeneity of landscape through some characteristics of crop pattern
38 and cultural practices. However, these characteristics are generally unknown
39 and are thus simulated using geostatistical methods and some localized and
40 costly field surveys. Consequently, information (even partial) on soil surface
41 condition between rows could be usefully introduced in such models. Users'
42 demands usually concern (1) vineyards location and delineation and (2) iden-
43 tification of some characteristics that can be connected to cropping practices
44 or crop quality, such as interrow width, row orientation, presence of grass be-
45 tween rows or missing vine plants (Montesinos Aranda and Quintanilla [2006]).
46 Many vineyard related studies in remote sensing (such as Lamb et al. [2004]
47 or Zarco-Tejada et al. [2005]) use the infrared channel of low spatial resolution
48 images to characterize vine vigour. On Very High Spatial Resolution (VHSR)
49 images, the plantation and training patterns (often in rows or grids) become
50 distinguishable, providing great discrimination and characterization poten-
51 tialities. However, realizing this potential with automatic processes requires
52 the development of new image processing approaches, allowing the analysis
53 of textured image. Two kinds of approaches have been used to that aim for
54 vineyard characterization: texture and frequency analysis. The former has re-
55 cently been used by Da Costa et al. [2007] to extract vineyards boundaries
56 from 0.15 cm resolution images. However, a main drawback of the approach
57 relies on the necessity to select a window inside each vine block before pro-
58 cessing and the efficiency of the method is not quantified since results were
59 qualitatively validated through a non-exhaustive visual control. Moreover, a
60 comparative study of methods for vineyards detection (Delenne et al. [2008a])
61 has shown the inferiority of such kind of textural approach in comparison with
62 a frequency analysis. This later, which takes advantage of the crop patterns
63 periodicity, has been successfully used by Wassenaar et al. [2002] who applied
64 a Fourier Transform to characterize already delineated vine blocks on 25 cm
65 resolution images. This approach also enables the accurate estimation of in-
66 terrow width and row orientation, which can be used to easily extract and
67 characterize each vine row, contrary to the complex and time-consuming clas-
68 sical methods of deformable models, such as used in Bobillet et al. [2003]. The
69 'vinecrawler' algorithm presented in Hall et al. [2003] and successfully applied
70 on Australian vineyards, would be difficultly usable in our case where vine
71 rows and interrows rarely contain more than two or three pixels (see section
72 'Study area and data'). This paper addresses the issue of vineyard detection,
73 delineation and characterization from VHSR aerial images using a frequency
74 analysis approach. The originality of the developed method stands in the fact
75 that it is entirely automatic and produces a geographic data base in a 'shape-

76 file' format, which can be integrated into any GIS used by vineyard managers.
77 The first part of this paper describes the proposed approach and the study
78 area. Considering that the main objective of this paper is to present the whole
79 workflow process, assessment of method efficiency is only presented for tests
80 done on the red channel of an aerial image with a 50 cm spatial resolution.
81 This choice (discussed in the section 'Study area and data') was guided by
82 the increasing availability of such images in Europe and by results obtained
83 in previous studies (Wassenaar et al. [2002], Delenne [2006]).

84 2 Material and method

85 In the following, the term 'parcel' will refer to an individual vineyard block
86 with homogeneous characteristics (row orientation, interrow width, agricul-
87 tural practice. . .). The process workflow can be divided in three main steps:
88 (1) vineyard detection, (2) initial parcel delineation, and (3) vine row extrac-
89 tion, allowing boundaries refinement. At each step, some characteristics are
90 derived, either to be directly added in the user's geographical database or to
91 be used in a further processing step.

92 2.1 Study area and data

93 The study area is the Roujan catchment (southern France), which has been
94 an experimental site for hydrological studies since the beginning of the 90's. In
95 this Mediterranean coastal plain, the diversity of agricultural practices leads to
96 a great heterogeneity among the vineyards to be detected on remote sensing
97 data. However, according to training mode, two main patterns can be ob-
98 served: grid or line. About a quarter of the vineyards considered in this study
99 are trained in 'goblet', involving no wire or other support system and leading
100 to a grid pattern, often square, with approximately 1.5×1.5 m spacing. The
101 line pattern concerns most of the recent vineyards, which are trained using
102 horizontal wires to which the fruiting shoots are tied. Spacing between vine
103 plants in the same row is smaller than spacing between rows (often 1×2.5 m
104 spacing in the study area). More adapted to mechanization, this nowadays
105 widespread training mode is named trellis or wire-training. Weed control prac-
106 tices in the study area are based on three main methods: chemical weeding,
107 mechanical weeding and grass cover. Cultural practices are characterized by
108 either applying the same weed control practice on each interrow or alternating
109 various weed control practices. The main combination modalities are: 1/1 (no
110 alternation of practices), 1/2 (e.g. interrows alternatively grass covered and
111 chemically weeded), 1/3 or 1/4. Data acquisition was made during the first
112 week of July 2005, when foliar development was such that both vine and soil

113 were visible on aerial photographs, providing enhanced pattern visibility. Dig-
114 ital cameras were used aboard an Ultra Light Aircraft to acquire RGB (three
115 channels in the visible part of the electromagnetic spectrum: red, green and
116 blue) and infrared images, with a spatial resolution of 50 cm. These character-
117 istics have been chosen because they correspond to largely available data in
118 Europe. Preliminary tests done on the Blue, Green, Red, Near Infrared chan-
119 nels and on the NDVI and Green-NDVI indices (Delenne [2006]) have shown
120 that best results are obtained with the Red channel. This is mainly due to the
121 fact that the contrast between vine rows (vegetation) and interrows is gener-
122 ally better in the red channel and especially when the interrows are covered
123 by grass. The influence of resolution has also been studied and it was demon-
124 strated that resolutions ranging from 30cm to 50cm were optimal according
125 to the interrow widths encountered (Delenne [2006]). Thus, only results of
126 the processing of the 50 cm resolution red channel will be presented in this
127 paper. For result validation, ground-truth information was collected at the
128 same time as image acquisition. The 121 vine parcels of the study area have
129 been digitized in a GIS database which also contains information concern-
130 ing land use and, for vineyards, characteristics of training mode (row or grid
131 pattern), interrow width, orientation and soil surface condition between rows
132 and under vine plants (covered by grass, chemically or mechanically weeded).
133 Reference row orientations and interrow widths were obtained by precise on-
134 screen measurements: row orientation was measured with a 1 precision and
135 interrow width was calculated by dividing the width of the whole parcel by
136 the number of interrows. In the following, this data base will be called the
137 reference database.

138 *2.2 Vine parcel detection and boundaries extraction*

139 This part is based on previously published works and is thus briefly recalled
140 here.

141 Fourier theory (named after Joseph Fourier) states that almost any signal,
142 including images, can be expressed as a sum of sinusoidal waves oscillating at
143 different frequencies. Thanks to the Fast Fourier Transform (FFT) algorithm
144 (Cooley and Tukey [1965]), the discrete Fourier transform of an image I can
145 be quickly computed. Its amplitude, or Fourier spectrum, can be represented
146 in the frequency domain as an image \hat{I} , symmetric with respect to its center.
147 Each position (u, v) in the Fourier spectrum corresponds to a particular spatial
148 frequency increasing the further it is from image center. A periodic pattern in
149 the spatial image I will induce a high value of the associated pixel in image
150 \hat{I} . The method is thus based on the fact that vineyards are, most of the
151 time, organized in rows or grid and induce very located peaks. The location of
152 these peaks also enables the precise estimation of row orientation and interrow

153 width, which will be useful in the next steps of vineyard characterization (see
154 section Results). Two methods, based on this principle, have been developed
155 for vineyard boundaries extraction: the first one, at an inner-parcel scale,
156 classifies each pixel in vine/non-vine using the FFT on its near-neighborhood
157 (about 30 m²) before segmenting the resulting image in vine parcels (Delenne
158 [2006] and Delenne et al. [2006]); the second one, at a more global scale, treats
159 image subsets (about 500 m²) containing several vine parcels at the same
160 time and performs the segmentation directly in a recursive process (Rabatel
161 et al. [2008] and Delenne et al. [2008b]). The first method is much simpler
162 to implement and provides equivalent results in terms of detected parcels but
163 with less accuracy in boundaries location.

164 2.3 *Vine row extraction: a way to improve delineation and characterization*

165 The characteristics of row orientation and interrow width are used in this step
166 to extract each vine row in the segmented parcel. The two main objectives of
167 this extraction are the improvement of boundaries location by a precise ad-
168 justment of each row and the foliar density characterization at row level (with
169 the out-coming detection of missing vine plants). Row extraction includes 3
170 steps: 1) identification of the rows inside the previously delineated parcels, 2)
171 adjustment of the vine row network and 3) use of the final network to improve
172 and complete the geographical database.

173 2.3.1 *Initial row network extraction*

174 The first step of vine row extraction consists in setting a row ‘network’ in-
175 side the previously segmented parcels. Assuming that rows are parallel, the
176 straightforward proposed approach firstly consists in filling the parcel with a
177 high number of oriented segments (e.g. spaced by half a pixel). Then, segment
178 corresponding to vine rows are selected using two constraints based on digital
179 numbers (DN) values and interrow width. In general, vegetation reflectance is
180 lower than soil one in red wavelengths. For vineyards, the pattern contrast is
181 sharpened in the red spectral band, thanks to the vine plants shadow located
182 under the row when the sun elevation is high. Based on the hypothesis that
183 vine row DN are lower than soil ones, local minima are first identified to select
184 vine rows. Some of these minima, which are not located on vine rows, are
185 eliminated using a second selection constraint based on a minimum interrow
186 width (Figure 1).

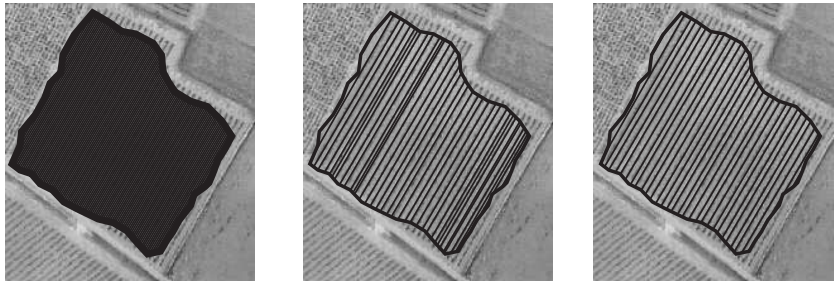


Fig. 1. Vine row detection. Left: row network initial setting; middle: elimination of false rows using the constraint of digital number local minima; right: further elimination using the constraint of minimum interrow width.

187 *2.3.2 Network adjustment on the parcel neighbourhood*

The row network is precisely adjusted using four actions: two row length adjustments, shortening and lengthening, and two adjustments of row number, elimination and addition. In the following, the two classes ‘row’ and ‘interrow’ are considered (the interrows being defined by translating the rows of half an interrow width, perpendicularly to row orientation). The general algorithm of this adjustment process is presented in Figure 2. For row length adjustment (shortening and lengthening), one meter length segments - corresponding to the mean interplant distance along a row encountered in the study area - are considered at row ends. The mean DN of a segment is compared to the DN distribution of the entire row and to the DN distribution of the both adjacent interrows using the Mahalanobis distance (introduced by P. C. Mahalanobis in 1936) defined by equation 1:

$$d_M = \sqrt{\frac{(v - \mu)^2}{\sigma^2}} \quad (1)$$

188 with v the value to test, μ and σ^2 the distribution mean and variance respec-
 189 tively. This distance (unlike the Euclidian one) is invariant to any change of
 190 scale and gives an estimation of the possibility for an element to belong to
 191 a class. Thus, if the segment mean DN is closer to the class ‘row’ than the
 192 class ‘adjacent interrows’, the segment is considered to belong to the row.
 193 Lengthening is first tested by adding a segment to the row until it is no more
 194 classified as ‘row’. If the initial lengthening fails, segment elimination is tried.
 195 Additional tests check the presence of interrow segments at both sides of the
 196 row to avoid some false detection due to objects having the same range of DN
 197 values as vine rows (such as trees). Once initial rows are adjusted, the next
 198 step consists in row elimination or addition based on the analysis of the whole
 199 row mean DN value. Concerning the elimination process, each row mean DN
 200 value is compared to the global distribution of the mean DN values of all the
 201 rows and interrows of the parcel. The removal occurs when the row mean DN
 202 value is closer to the interrows class than the row one. The same kind of test
 203 is carried out to try to add some rows at the edges of the parcel.

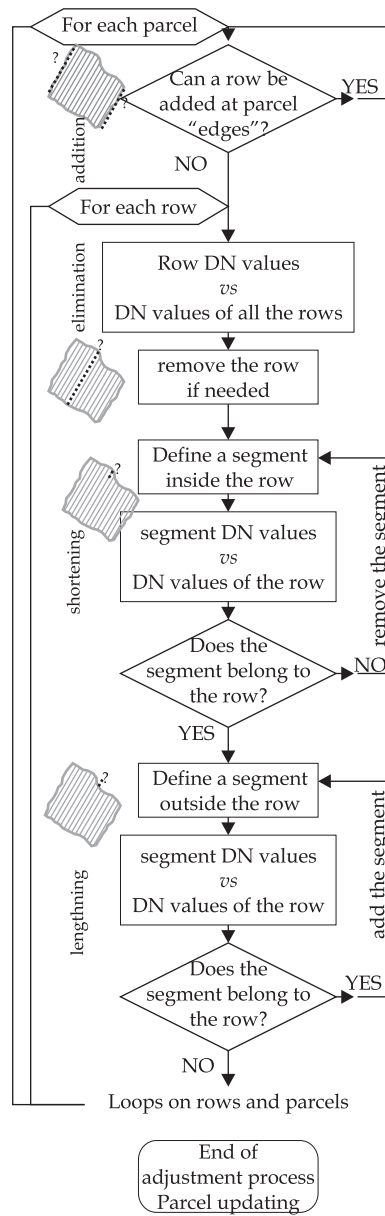


Fig. 2. chart of the adjustment process.

204 *2.3.3 Parcel update in the geographical database*

205 When all the rows have been adjusted, the parcel boundaries need to be cor-
 206 rected accordingly. At this stage, if some rows belonging to different parcels
 207 but having the same orientation and interrow width overlap each other, the
 208 corresponding parcels are grouped. This enables the correction of some over-
 209 segmentation cases. On the contrary, when more than three consecutive rows
 210 have been eliminated, the parcel is split up into two new parcels. This en-
 211 ables the correction of some under-segmentation cases. Figure 3 shows some
 212 improvements of parcel delineation after row detection and adjustment (see
 213 section Results for more details).

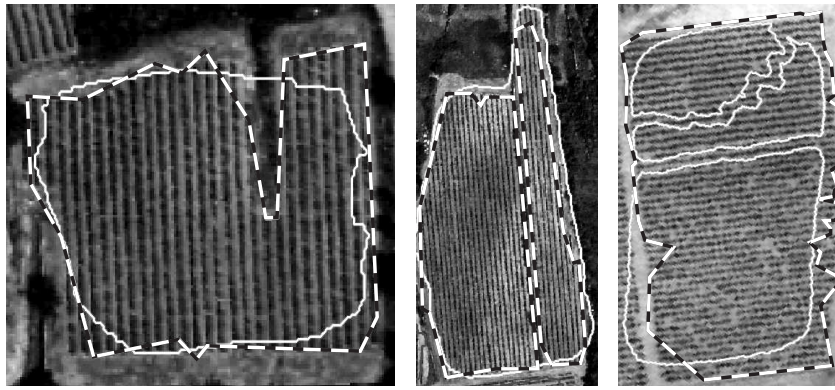


Fig. 3. Parcel boundaries improvement thanks to row adjustment (left), elimination (middle) and addition (right). Continued lines: initial boundaries; discontinued lines: adjusted ones.

214 2.3.4 *Detection of missing vine plants*

215 The missing plant detection is processed in a similar way as row length ad-
 216 justment. Each row is divided in 1m length segments and the mean DN value
 217 of each segment is compared to the DN distribution of the row and the both
 218 adjacent interrows. When the distance to the interrow class is smaller than
 219 the one to the row class, the segment is considered to correspond to a miss-
 220 ing vine plant. The non-detection of missing vine plants can be due to the
 221 presence of grass under the row (so that the interrow radiometry is close to
 222 the row one) or to the fact that the gap has been filled by the two neighbour
 223 plants. On the contrary, some plants can be wrongly considered as missing for
 224 several reasons: the missing vine plant has been recently replaced and is not
 225 yet visible on the image; the plant is not missing but is not very sturdy; the
 226 interrow is covered by grass so that the difference between row and interrow
 227 is poor... (see section Results for more details).

228 2.3.5 *Soil surface characterization: alternation of weed control methods*

229 When alternation of weed control methods is observed, another periodical pat-
 230 tern appears on the image with a frequency twice or three or four times smaller
 231 as the one characterizing the row (according to the combination modality).
 232 To automatically assess this secondary pattern, the one dimensional Fourier
 233 transform is computed for each parcel on the signal made by the interrows DN
 234 means. Then, knowing the interrow frequency f , the process seeks for a second
 235 local maximum and estimates its frequency f_2 . There will be alternation if the
 236 frequency f_2 is approximately equal to $f/2$, $f/3$ or $f/4$.

Case	Meaning
1. Good segmentation	The common covering surface is higher than 70% of both manually and automatically segmented parcels.
2. Over-segmentation	Several parcels are automatically segmented within one real parcel.
3. Under-segmentation	One automatically segmented parcel includes several real parcels.
4. Partial segmentation	Only one part of the real parcel is detected.
5. Larger segmentation	The automatically segmented parcel spills over one or more parcels.
6. Missing segmentation	Vine parcels not automatically segmented.
7. Extra segmentation	Non-vine parcels automatically segmented as vine.
8. Other cases	All other cases such as both over and under segmentation or both under and partial segmentation.

Table 1

Segmentation result classification: 8 different cases can be considered.

237 3 Results

238 3.1 Segmentation results before and after row adjustment

239 For the validation process, the results of vine parcel segmentation are classified
 240 using the 8 different cases defined in Table 1, according to their compliance
 241 with the reference boundaries (see Rabatel et al. [2008] for more details).

242 Segmentation results obtained on the red channel of the image are presented
 243 in Table 2 before and after row adjustment. These results have been obtained
 244 with the first cited approach (Delenne et al. [2006]). As presented in Rabatel
 245 et al. [2008], On the former results, only 12 parcels (10%) are not detected,
 246 all of them - except one - being smaller than 0.5 ha and thus leading to weak
 247 amplitude peak in the Fourier spectrum. Even the very young parcels of the
 248 study area (less than three years old) have been detected, thanks to the en-
 249 hancement of the image contrast. Nearly half the parcels have been correctly
 250 segmented (case 1), and many have been under (14.8%) or partially segmented
 251 (10.7%). As shown in the second column of Table 2, the rows detection and
 252 adjustment process enhances these first results in many ways, leading to a
 253 raise of correctly segmented parcel rate from 48% to 56.2%. No further im-
 254 provement step can be envisaged concerning the case of missing segmentation,
 255 which contains one more parcel after a too important shortening of its rows.
 256 However, this case concerns less than 5% of the study area and these kinds

Case	Before row adjustment	After row adjustment
1. Good	58 (48 %)	68 (56.2%)
2. Over	3 (2.5%)	1 (0.8%)
3. Under	18 (14.8%)	19 (15.7%)
4. Partial	13 (10.7%)	9 (7.5%)
5. Larger	8 (6.6%)	3 (2.5%)
6. Missing	12 (10%)	13 (10.7%)
7. Extra	7 (-)	3 (-)
8. Other	9 (7.4%)	8 (6.6%)

Table 2

Segmentation results (in parcel and percentage) obtained on the red channel of a 50cm resolution image, before and after row adjustment, for the 121 vine parcel of the Roujan study site.

257 of small parcels tends to be no more exploited due to the general increase of
258 mechanization.

259 3.1.1 Characterization results

260 **3.1.1.1 Interrow width and row orientation** Between on-screen mea-
261 surements and method-derived estimates, average absolute differences of less
262 than 1° and 3.3 cm have been found respectively for row orientation and
263 interrow width. As shown in Figure 4, the coefficients of determination R^2
264 obtained when comparing computed parameters to reference data are almost
265 equal to 1 for both characteristics. Moreover, it could be visually assessed in
266 the step of row extraction that the reference rows orientations (obtained by
267 photo-interpretation) are less accurate than the automatically computed ones.

268 **3.1.1.2 Missing vine plants detection** Figure 5 shows some examples
269 of results obtained with the proposed method. An exhaustive validation could
270 not be done because of the lack of ground data. The following classification
271 (done by photo-interpretation) is thus used: (1) less than 15% of missing vine
272 plants, (2) between 15% and 30%, (3) more than 30%. The confusion matrix
273 of this classification is given in Table 3 for all the vine parcels of the study
274 area except seven very young vineyards for which vine plants are not visible
275 by photo-interpretation. These results are very satisfactory since 92% of the
276 parcels have been well classified. This kind of information will be useful for
277 vineyard managers, for example to target the parcels which will need a more
278 specific attention.

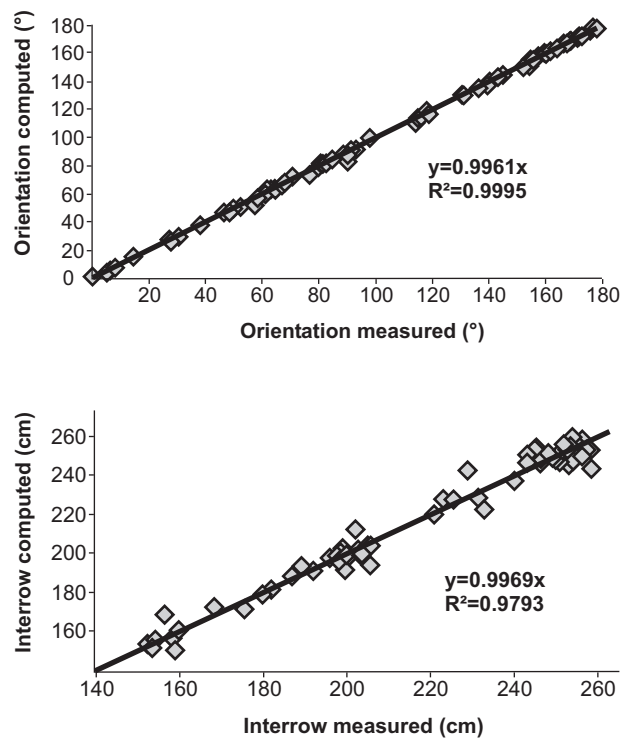


Fig. 4. Interrow width and row orientation: on-screen measurements vs automatic estimation.

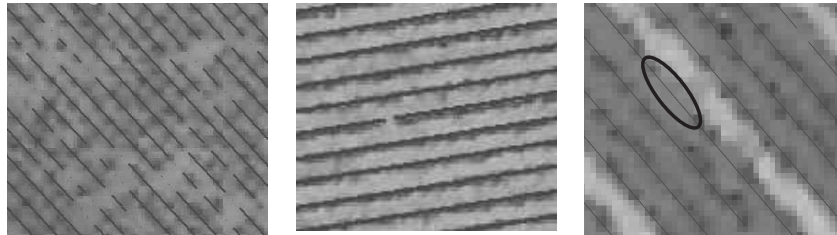


Fig. 5. Examples of missing vine plants detection. Image subsets in parcels having more than 25% (left) and less than 15% (middle) of missing plants; detection error due to the presence of grass under the row (right).

279 **3.1.1.3 Soil surface characterization: alternation of weed control**
 280 **methods** Confusion matrix for ‘alternated parcels’ detection is given in Ta-
 281 ble 4. 81% of the 121 parcels have been well classified. Nearly all the classifica-
 282 tion errors concern alternated parcels for which the periodic pattern is poorly
 283 contrasted in the image (Figure 6a). As a consequence, results obtained concern-
 284 ing parcels with some interrows covered by grass are much satisfactory,
 285 with only 4 wrong classifications over 18. The two non alternated parcels which
 286 have been wrongly classified contain some interconnecting farm roads, which
 287 induce a secondary and confusing pattern.

	< 15%	15% < - < 30%	> 30%
< 15%	82	4	0
15% < - < 30%	1	14	1
> 30%	2	1	9

Amount of correct classifications: **105/114 (92%)**

Table 3

Confusion matrix concerning vineyard classification in three classes according to their rate of missing vine plants (automatic process in line, photo-interpretation in column).

	1/1	1/2	2/3	3/4
1/1	85	16	2	0
1/2	1	13	0	0
2/3	0	0	0	0
3/4	1	0	0	3

Amount of correct classifications: **98/121 (81%)**

Table 4

Confusion matrix concerning vineyard classification according to their cultural practice (alternation of weed control methods). Automatic process in line, photo-interpretation in column.

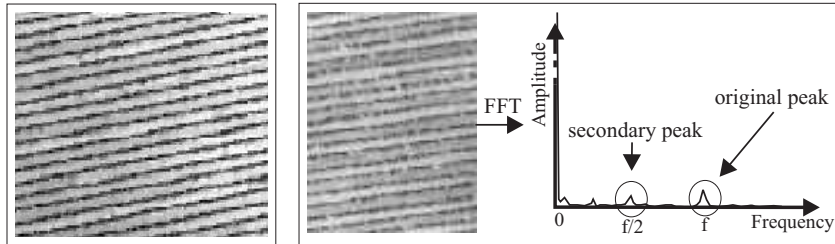


Fig. 6. Left: example of an undetected alternation 1/3 (invisible at naked eye); right: example of an alternation 1/2 and its Fourier spectrum.

288 4 Discussion and conclusions

289 In this study, a comprehensive process for vineyard detection, delineation and
 290 intra-parcel characterization has been proposed. The main advantages of this
 291 method are: its easy implementation, processing speed and the limited amount
 292 of parameters. It has been implemented in a completely automatic way and
 293 exports results into GIS format (.shp) with an associated database containing
 294 characteristics such as area, perimeter, interrow width, row orientation, miss-
 295 ing vine plants rate and cultural practices. This process, easily integrated in
 296 the GIS used by vineyards managers, will enable a considerable reduction of

297 the cost previously needed to obtain all these characteristics using on-ground
298 surveys or photo-interpretation. Indeed, the survey done for the validation
299 of this study took two days when it only consisted in checking several char-
300 acteristics of the parcel without carrying out the differential GPS survey of
301 boundaries. Meanwhile, only about one hour is needed for the automatic pro-
302 cess on a personal computer, which may be the same for a manual digitization
303 but do not need such user intervention. Moreover, it has been shown that the
304 automatic estimation of vine row orientation and interrow width are more ac-
305 curate than those obtained by photo interpretation or ground measurements.
306 As the method description is relatively long, we have chosen to present only
307 the best results, obtained with the red channel of the image. These make us
308 confident regarding the interest of the method as only 10% of the vine parcels
309 have not been detected in the first step of segmentation, mainly concerning
310 small parcels which tend to be no longer exploited due to their inadequacy
311 with the general mechanization used in viticulture. Although not validated
312 exhaustively, the missing vine plant detection seems to be correctly assessed
313 as 92% of the parcels have been correctly classified according to three classes
314 of missing plants rate. The results of cultural practices characterization are
315 slightly poorer, except concerning practices involving grass cover. As said in
316 introduction, this information, even partial, will be useful to introduce in dis-
317 tributed hydrological models. As a perspective, a complete evaluation of the
318 method according to different types of input data (resolution, spectral bands,
319 Lidar data. . .) will be done and presented in a further paper.

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