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Vineyard detection from unmanned aerial systems images

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ABSTRACT

In viticulture, the adoption of precision agriculture techniques is nowadays increasingly essential to reach required high product quality standards. New reliable tools for mapping crop variability indexes in a vineyard or a single parcel are necessary to deploy site-specific management practices. In this paper, a new method to automatically detect vine rows in gray-scale aerial images is presented. The developed image processing algorithm is constituted by three main steps based on dynamic segmentation, Hough Space Clustering and Total Least Squares techniques. The procedure's reliability has also been proven in the presence of disturbance elements, like dense inter-row grassing, bushes and trees shadows, by properly detecting vine rows in the vineyard images. Moreover, its adaptive features allow it to obtain optimal results in the presence of uneven image illumination due, for example, to the presence of clouds or steep terrain slopes. The extracted row and inter-row information, besides being the basis for vineyard characterization maps computation, like vine plants vigor maps, could also be used as a reference for other precision viticulture tasks such as, for example, path planning of unmanned ground vehicles.

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1. Introduction

Nowadays, required high quality standards impose to many farms and growers the adoption of precision agriculture techniques and site-specific management practices (Kropff et al., 1997; Zhang et al., 2002; Stafford, 2006; Gonzalez et al., 2011). This is especially true in modern viticulture, where the possibility to distinguish between zones of different grape quality within the same parcel and to execute appropriate management according to inherent crop variability could provide for an increase in economic benefits and a reduction of the environmental impact (Arnó et al., 2009). The implementation of a precision viticulture (PV) approach to vineyard management is a process that begins with the observation of vineyard performance and associated vineyard attributes, followed by the interpretation and evaluation of the collected data (Proffit et al., 2006; Tisseyre et al., 2007; Bramley and Reynolds, 2010).

Remote sensing is one of the most powerful tools in PV, being able to rapidly provide a description of grapevine shape, size and vigor over entire vineyards, and to find relationships between these canopy descriptors and grape quality and yield (Lamb et al., 2004; Hall et al., 2008a, 2008b, 2011). The applications of satellite or airborne imaging in PV have nevertheless been limited by poor revisiting times, coarse spatial resolutions, high operational costs and complexity, and lengthy delivery of products (Zhang and Kovacs, 2012). With recent technological advances in aerospace engineering, the acquisition of Earth surface images at a low altitude (Low Altitude Remote Sensing system – LARS) by using Unmanned Aerial Systems (UAS) is being promoted as a suitable alternative for this purpose. This technology allows the acquisition of ultra-high spatial resolution aerial maps with low operational costs and near real-time image acquisition (Zhang and Kovacs, 2012).

To calculate vegetation indexes from aerial images, detection of vineyard plot is first needed, in order to obtain vineyard maps "cleaned" from all the features that are usually present in field aerial photography, such as roads, trees and bushes. Nonetheless, the extraction of pure vines pixels, discarding inter-rows areas, is crucial for enhancing the final vineyard maps quality and effectiveness for site-specific management (Hall et al., 2003; Kazmierski et al., 2011; Puletti et al., 2014). This task is usually complex and user-intensive, since the reflectance response of all these features is often similar to the canopy to be extracted. Many remote sensing systems and algorithms have been devised to study canopy

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Notation table

DN	Digital Number
FFT	Fast Fourier Transform
HPS	Hough Parameters Space
HT	Hough Transform
LARS	Low Altitude Remote Sensing
NDVI	Normalized Difference Vegetation Index
NIR	Near InfraRed
PV	precision viticulture
ROI	region of interest
TLS	Total Least Squares
UAV	unmanned aerial vehicle
UAS	Unmanned Aerial System
UGV	Unmanned Ground Vehicle
A	group of interconnected pixels (Cluster) after first clustering
$\mathcal{A}$	set of all detected clusters A in the processed image after first clustering
B	group of interconnected pixels (Cluster) after vine rows detaching
$\mathcal{B}$	set of all detected clusters B in the processed image after vine rows detaching
d	diagonal of the image (in pixel)
$f(r)$	sum of the Euclidean distances between the line r and the pixels $(x_i, y_i) \in A, i = 1,\ldots,M$
H	maximum value of $S(\cdot)$
$I(\cdot)$	projection of $S_H(\cdot)$ values on the θ axis
$J(\cdot)$	normalized inertia moment of the intensity distribution histogram of $\Omega_{x,y}$
l_w	sliding window size, used to select $\Omega_{x,y}$
l	rectilinear line detected with HT
$\mathfrak{L}_A$	set of all rectilinear lines detected in a cluster A
N	number of pixels in $\Omega_{x,y}$
$n(v)$	number of pixels characterized by DN intensity value v
n_w	number of times that the neighboring window segmentation process is applied to a pixel (x, y)
m	number of $\hat{\theta}$values in $\mathcal{O}_A$
M	number of pixels in A
$\mathcal{O}_A$	set of most recurrent values of $\hat{\theta}$ in cluster A
p	generic pixel εA
$\mathcal{P}_{\hat{\theta}}$	set of most recurrent values of ρ, for a fixed $\hat{\theta}$ value, in cluster A
q	point (ρ,θ) in HPS
Q	root mean square total error of $\hat{r}$
r	line detected with TLS
$s(p)$	curve in HPS, derived from p
$S(\cdot)$	function defined as the number of curves $s(p)$ that pass through the neighborhood $Z(\cdot)$
s_i	Projection of pixel i in the HPS
s_w	sliding window moving step, used to select $\Omega_{x,y}$
T_Q	threshold of Q
T_J	threshold of $J_{x,y}$
T_θ	threshold of difference between inclination angles θ between two lines
T_d	threshold of distance between the nearest two ends of the segments
w_ρ	reciprocal of ε_ρ
w_θ	reciprocal of ε_θ
$Z(\cdot)$	neighborhood in the HPS
ε_ρ	width of Z on the ρ axis
ε_θ	width of Z on the θ axis
θ	clockwise inclination angle with respect to the vertical axis
$\hat{\theta}$	most recurrent values of θ
Θ	set of θ values used for HPS tasselation
$\mu_{x,y}$	mean of the intensity distribution histogram of $\Omega_{x,y}$
ρ	distance from the origin of the image
P	set of ρ values used for HPS tasselation
$\Omega_{x,y}$	subset of pixels centered in pixel (x,y)

reflectance response (Zarco-Tejada et al., 2005), but the possibility of exploiting the information potential of the images depends on the development of image processing methods for analyzing textured images (Delenne et al., 2010). Starting from simple value thresholding techniques (see e.g. Hall et al., 2003), many methods have been developed to face the problems of vine rows and vineyard detection, either with texture or frequency analysis. Vine rows and parcels detection are strictly related since in most cases vine plots are identified using row information. Ranchin et al. (2001) proposed a method based on wavelets and multi-resolution analysis that obtained, on average, a score of 78% of correctly identified plots, although it is complex and requires significant user intervention. Da Costa et al. (2007) proposed a method which takes into account the textural properties of vine images, where a thresholding operation on textural attributes allows discriminating between vine field and non-vine field pixels. With a different approach, using the typical periodic patterns of this crop, Delenne et al. (2006) and then Rabatel et al. (2008) introduced a recursive process based on the Fast Fourier Transform (FFT) and the Gabor filtering of the aerial images to show the delineation of vineyard plots and the evaluation of row orientation and inter-row width. Some factors, such as alternate treatments between inter-rows and high numbers of vines which are missing or too young, had the consequence of compromising the periodicity of the vine row patterns and then, consequently, performance degradation. More recently, Delenne et al. (2010) improved the performance of their vine plot detection method, based on the FFT and the frequency domain Gabor filtering, by enhancing the precision of the boundary locations with a precise adjustment of each row (still, the method presents an over-estimation of the vine parcels in case of missing vines). An active contour model developed by Bobillet et al. (2003) aims at fitting a line to each vine row through a global convergence process. However, the limit of this method lies in the initialization process, essential to reach the optimum of the convergence process, which requires segments to be placed as close to the underlying vine rows as possible. This problem has been solved by defining a model of roughly parallel and equidistant lines, although this approach limits the application area of the method, excluding less regular vineyards.

With a different approach, Smit et al. (2010) proposed a segmentation method that combined a thresholding technique with a subsequent graph-based analysis. This method provided good results in the case of a flawless segmentation step, which requires a manual setting of image pre-processing parameters and threshold values, but it had difficulties in managing the presence of non-vine vegetation near the parcels and within the inter-rows.

The objective of the method proposed in this paper is to use information collected in high-resolution aerial digital images to determine:

1. A mask which identifies all the pixels that represent vines foliage and discriminates the vineyards from the background comprising of inter-row soil and grass, bushes, trees and other elements of the rural area.

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