A Pilot Digital Image Processing Approach for Detecting Vineyard Parcels in Douro Region through High-Resolution Aerial Imagery

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ABSTRACT

Vineyard parcels delimitation is a preliminary but important task to support zoning activities, which can be burdensome and time-consuming when manually performed. In spite of being desirable to overcome such issue, the implementation of a semi-/fully automatic delimitation approach can meet serious development challenges when dealing with vineyards like the ones that prevail in Douro Region (north-east of Portugal), mainly due to the great diversity of parcel/row formats and several factors that can hamper detection as, for example, interrupted rows and inter-row vegetation. Thereby, with the aim of addressing vineyard parcels detection and delimitation in Douro Region, a preliminary method based on segmentation and morphological operations upon high-resolution aerial imagery is proposed. This method was tested in a data set collected from vineyards located at the University of Tr ́as-os-Montes and Alto Douro(Vila Real, Portugal). The presence of some of the previously mentioned challenging conditions - namely interrupted rows and inter-row grassing - in a few parcels contributed to lower the overall detection accuracy, pointing out the need for future improvements. Notwithstanding, encouraging preliminary results were achieved.

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CCS Concepts

• Applied computing → Agriculture; ˆ Computingmethodologies → Image processing; ˆ Information sys-tems → Geographic information systems.

Keywords

Vineyard parcel; Zoning; Automatic Vine Parcelling; DigitalImage Processing; UAV; UAS; RGB

1. INTRODUCTION

Vine parcelling towards viticultural zoning constitutes the preliminary step for significantly important activities such as propriety assignment, cultures characterization and landuse management and planning. However, in the literature concerning automatic detection of vineyard elements, works focusing vine rows processing seem to be more frequent than the ones addressing vineyard parcelling.

Regarding the works associated to vineyard rows detection, Bobillet *et al.* [1] proposed a method based on active contour model. Comba *et al.* [2] combined dynamic segmentation, Hough Space Clustering and Total Least Squares techniques with good results, even in the presence of disturbance elements (inter-row grassing, shadows, etc.). Same techniques were applied by Primicerio *et al.* [3] in multispectral images processed with normalized difference vegetation index (NDVI). Later, Primicerio *et al.* [4] went further and applied a multi-logistic model for the detection of missing plants in vine rows. Nolan *et al.* [5] described a way of detecting vine rows with skeletonisation techniques. Other works similarly aligned with this context can be found using different strategies such as row detection involving Ward's modified technique [6], vine/non-vine discrimination through crop surface models production [7], performance comparison between classification approachesfor vines canopy estimation on vertical trellis systems [8] andvineyard rows characterization based on dense point cloud[9].

On the other hand, semi-/fully automatic vine parceling approaches seems to be harder to find. Delenne *et al.* [10] reported a methodology focusing vineyards delineation in Languedoc-Roussillon region (southern France), based on their previous methods using Fast Fourier Transform (FFT)[11, 12] and image subsets with recursive segmentation [13,14]. Another work was presented by Adam *et al.* [15] who combined lidar data with a focal statistics method. Karakiziand Karantzalos [16] developed an object-based detection and discrimination framework operating with very high resolution pan-sharpened satellite data, which was validated on four different viticulture regions in Greece. Regarding vine parcels detection, a standard nearest neighbour classifier was adopted. Recently, a machine learning-based approach combining superpixels and supervised classification was proposed [17], also using satellite imagery.

Acknowledging vine parcelling importance, the aforementioned scarcity of approaches addressing this topic and, also, the numerous vineyard morphologies that can be found in Douro's demarcated region constitute the motivation for this paper, in which an alternative method for detecting vine parcels out of high-resolution aerial imagery is presented. This method is still in an early development stage, but promising preliminary results were achieved by processing images collected with an unmanned aerial vehicle (UAV),whose flights were carried out over vineyard fields located at the University of Tr ́as-os-Montes and Alto Douro (UTAD- Vila Real, Portugal).

Regarding paper's organization, next section will provide some details regarding the images that were collected and used for further processing. Section 3 describes the method used for processing UAV collected images with the goal of detecting vine parcels. Some results are provided in Section4, just before the final one (Section 5) that is reserved for conclusions and remarks announcing future developments.

2. AERIAL IMAGERY CHARACTERIZA-TION

Douro Region has a wide variety of vineyard formats, with many delineations and several frontiers with each others. Their rows can be rectilinear or curvilinear and each one of them can be simply or pair-wisely arranged. Moreover, it is quite common to find several vine parcels with missing vine plants within the same row and/or inter-row vegetation connecting two parallel rows within the same vine parcel. All of this heterogeneity turns out to be a convenient case study to exploit digital approaches for automatic features extraction.

Considering the early stage of this study in particular, a simpler imagery data set collected at UTAD campus, more specifically in Nossa Senhora de Lourdes farm (41°17'08.7"N7°44'12.2"W), was used. This area is mainly composed of vineyard parcels - besides other much less predominant crops such as maize, a hazelnut orchard, olive trees and other fruit trees - and its surface height is practically homogeneous. At acquisition moment, some of those parcels had interference of inter-row vegetation and/or interrupted rows. Figure1 depicts the imagery used in this study, with a semi- transparent yellow layer highlighting the targeted vineyards. A fixed-wing UAV senseFly eBee (senseFly SA, Loussagne, Switzerland) was used to carry out the data acquisition missions. Flight planning operations were configured using eMotion software. Flight height and overlap were respectively set

Figure 1: Study area, located at Nossa Senhora deLourdes farm (41°17'08.7"N 7°44'12.2"W), nearbythe campus of the University of Tr ́as-os-Montes eAlto Douro. Semi-transparent yellow layer high-lights the targeted vineyards.

up to 175 m and 75%, while area-related parameters were defined to reach $\approx$12 ha of land covering. A resulting ground sample distance (GSD) of $\approx$5 cm was obtained. To perform the RGB imagery acquisition during the mission, a Canon IXUS 127 HS camera was placed on-board of the UAV.

Acquired data photogrammetric processing was carried out in Pix4Dmapper Pro (Pix4D, Lousagne, Switzeland).This software is capable of dealing with different electromagnetic spectrum imagery and their potential distortions. To perform photogrammetric processing, it was used a laptop with the following characteristics:

- an Intel i7-4720HQ central processing unit, running at 2.6 GHz;
- 16GB of Random Access Memory (DDR3, 1600 MHz);
- NVidia GeForce GTX 970m (3GB GDDR5 5000 MHz) graphic card.

Acquired RGB imagery was imported to Pix4D and a traditional photogrammetric processing pipeline was applied: firstly, dense point clouds were created and, then, the orthophotomosaics were obtained, followed by digital surface models.

Next section will present the method proposed in this paper, which accepts corrected orthophoto mosaics as input and manages to find vineyard parcels by automatically processing the features present in the image.

3. METHOD PROPOSAL

At this development stage, the proposed method for vineyard parcelling works with four main groups of steps, as itis portrayed by Figure 2: basic segmentation, region proprieties analysis, cleaning of loose pixels and division of objects into groups of orientation and, lastly, vine parcels handing. Matlab (MathWorks Inc, Massachusetts, United States of America) has been the supporting tool for implementation. After image loading, the first group of operations carries out color space manipulation in which

RGB image is converted Hue-Saturation-Value (HSV). Then, image greenness is filtered through band "H" to keep vegetation and dispose everything else (replaced with black color). Image is reconverted to RGB colour space, followed by an adaptive threshold application based on local information.

During the region proprieties analysis, objects are splitted by clusters of white pixels and the following features are extracted: region of interest image and bounding box (for object's isolated processing and further original position retrieval),area in pixels (towards small objects removal), centroid, orientation, major/minor axis length and eccentricity(allowing rough row characterization), as well as convex hull(for row contact testing).These objects are gathered in arrays of structures holding previously extracted features, which are then submitted to the next step: cleaning and grouping by orientation. Cleaning will delete the rows with small eccentricities, min axis lengths and areas. By analysing the objects of a 2604x1613px image (downsampled from 8680x5436 px for processing burden decreasing purposes) with 5 cm of GSD, the following threshold values were established: 0.92 for *excentricity_treshold* ratio; 3px for *min_axis _treshold*; and 15 px *row_area_treshold*.

The division of orientation groups intends to simplify the processing and decrease the probability of overlapping rows belonging to different vineyards. Thus, rows are grouped by $\pm\theta$ degrees. θ selected in this approach was 18°, which enables dealing with up to 20 different groups. Finally, vine parcels handling takes place. For each orientation group, an image is created and burned with their respective rows. Then, a dilation is performed to force neighbor rows to contact. Dilation has well-known mathematical definition, as it is pointed out by equation 1:

$$A \oplus B = \left\{ z \middle| \left(\hat{B} \right)_z \cap A \neq \varnothing \right\} \qquad (1)$$

where B and $\hat{B}$ refer to a structuring element affecting a pixel set z, reflectively. A perpendicular line – relatively to each row - was the structuring element used to perform the described operation. 25 px was the scalar that came out from the 2604x1613 px (downsampled) image analysis, to maximize side-by-side rows contact preventing, simultaneously, unintended connections with rows having similar orientations in the neighbour groups.

After applying dilation to the whole groups set, rows are tested for contact - with a polygon intersection algorithm -assigning the touching ones to independent structures representing vineyard parcels. When rows aggregation task is over, delimiting polygon is calculated for each one of those parcels - based in extremity rows -, resulting in the respective estimated area. A clean-up is performed in the end to discard vineyards with less than 5 objects.

Proposed method was tested against ground-though to assess its precision in detecting vineyard parcels. Results are shown in the following section.

4. PRELIMINARY RESULTS

To preliminarily test the accuracy of the method, twelve vineyard parcels belonging to the study area that can be seen in Figure 1 were numbered from 1 to 12 and manually delineated to produce ground-truth masks. Concurrently, method's pipeline was used to process the image and estimate vineyard parcels, considering the same numbering plan. Percentages of overlap between ground-truth and estimated vineyard parcels were then assessed through Dicesimilarity coefficient. Table 1 presents the analytical results that are also visually depicted in Figure 3.

As it turns out, ground-truth and estimated vineyard parcels overlap range is between around 33 and 94%. Such disparity can be explained with the presence of inter-row vegetation and with the absence of vine vegetation in many rows, both affecting the performance of the proposed method.

On the one hand, inter-row vegetation ends up to form bigger clusters after image dilation, which are discarded when the eccentricity test is performed, resulting in severe underestimations, as it can be observed in vineyard parcels1 and 2, in which only 33.63% and 64.46% of detection rate(respectively) was achieved.

On the other hand, the lack of vines' vegetation also leads to the method's performance decrease, as it occurs in those cases characterized by the presence of inter-row vegetation, but due to opposite reasons. More specifically, image dilation may fail its goal of bonding some neighbour vine rows due to fragmentation. Underestimation in such conditions can be observed in vineyard parcel 11, wherein the lack of vines' vegetation ended up to result in a detection rate of≈78%.

Another phenomenon deriving from situations involving inter-row vegetation and/or vine rows interruptions that may take place is sub-parcelling, i.e., an unintended and uncontrolled event characterized by the division of vineyard parcels into smaller parts. Typically, sub-parcelling occurs when image dilation and subsequent polygon intersection tests merge two or more groups of rows that should be part of the same vineyard parcel. For example, the proposed method splitted vineyard parcel 11 into 4 sub-parcels, mainly due to several vine vegetation interruptions that resulted in vine rows fragmentation.

Notwithstanding the aforementioned issues, an average accuracy of 76.48% was achieved for the tested data set.

5. CONCLUSIONS AND FUTUREWORK

In this paper, a preliminary method for automatically detect vineyard parcels based on segmentation and morphological operations - such as dilations - was presented. This work intended to constitute a starting point to address more complex cases regarding Douro's vineyards, which typically have different morphologies. Together with the lack of vines' vegetation as well as the presence of plants between rows, such features represent a real challenge for automatic image based processing approaches.

The proposed pipeline mainly relies in image segmentation, elliptical objects filtering through eccentricity and transversal axis length measurements, dilation operations and polygon intersection tests to find clusters of vine row portions constituting vineyard parcels. Method's results are encouraging in what regards to vineyards that have a complete set of rows and absent inter-row vegetation, but the opposite conditions reveal that more work needs to be done. Therefore, the possibility of mitigating current method's issues with convolutional neural networks (CNNs) is being considered for future applications. To that end, powerful tools - e.g. Tensor Flow [18] and Keras [19] - capable of streamlining machine-based training/prediction of vineyards with different morphologies and in diverse vegetative conditions are available.

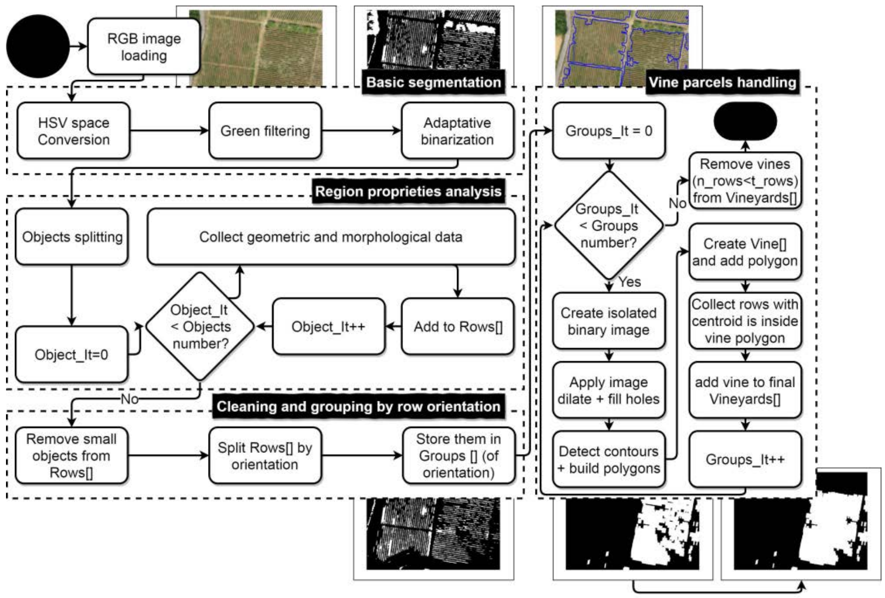

Figure 2: Proposed method flowchart, composed of four main groups of steps: basic segmentation, regionproprieties analysis, cleaning of loose pixels and division of objects into groups of orientation and, finally,vine parcels handing.

Figure 3: Binary mask - resulted from the applica-tion of the proposed method - overlapped to ground-truth mask, providing a visual insight of the meth-ods' accuracy.

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ID	Control Area (px^2)	Control Area (ha)	Test Area (px^2)	Test Area (ha)	Dice Sim. Corr. (%)	Sub-parcelling
1	1,384,891	0.35	476,988	0.12	33.63	2
2	2,196,294	0.55	1,471,729	0.37	64.46	2
3	1,206,321	0.30	1,123,091	0.28	88.79	1
4	818,283	0.20	482,040	0.12	46.61	1
5	1,034,356	0.26	1,022,438	0.26	93.86	1
6	1,330,266	0.33	1,275,414	0.32	92.49	1
7	2,197,594	0.55	1,798,897	0.45	80.55	2
8	1,106,894	0.28	995,252	0.25	85.53	1
9	1,733,591	0.43	1,604,501	0.40	89.61	1
10	1,752,339	0.44	1,464,909	0.37	79.82	2
11	1,474,603	0.37	1,227,926	0.31	78.47	4
12	698,302	0.17	448,771	0.16	83.96	2

Table 1: Accuracy results of the proposed method to detect vineyard parcels. Ground-truth and automaticallydetected vineyard parcels' areas are presented (in pixels and hectares) along with correlation percentages(calculated with Dice similarity coefficient) and sub-parcelling data (i.e., the number of parts in which a givenparcel is divided after the proposed method application).

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