DETECTING AND CLASSIFYING VINE VARIETIES FROM VERY HIGH RESOLUTION MULTISPECTRAL DATA

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ABSTRACT

In order to exploit operationally remote sensing data for agricultural applications efficient and automated methods are required towards the accurate detection of vegetation, crops and different crop varieties. To this end, an object-based classification framework has been developed and validated towards the detection of vineyards and the discrimination of vine varieties. Very high resolution satellite data were collected over four wine-growing regions in Greece during a three-year period, *i.e.,* 2012 to 2014. A rule-based classification scheme based on fuzzy logic was employed in order to firstly detect the vine parcels in the pan-sharpened multispectral satellite images. Then the canopy of each parcel was detected and separated from the soil in-between the vine rows. The detection of the different vine varieties followed based on a supervised classification procedure and spectral features. The overall validation and quite promising experimental results indicated that a throughout sensitivity analysis can form efficient operational tools for variety-based data analysis in precision viticulture.

Index Terms— Image classification, OBIA, Precision Viticulture

1. INTRODUCTION

Multispectral and hyperspectral sensors onboard satellite, aerial and UAV platforms are dominating nowadays in most precision agriculture acquisition systems. In order to exploit operationally these big earth observation data for agriculture and precision farming applications, efficient and automated processing methodologies are required that can detect accurately vegetation, crops and crop varieties in remote sensing images.

In particular for viticulture applications the Vitis vinifera L. vine varieties which are cultivated worldwide are numerous. Moreover, their management, grape/wine quality potential and respective economic value is variety dependent [2],[4]. Therefore, the detection of vineyards in satellite remote sensing data and the remote discrimination of vine varieties are of major importance for farmers, wine producers, geospatial engineers and government activities.

For more than a decade now research efforts are focusing on the exploitation of satellite imagery at different spatial, spectral and temporal resolutions towards the efficient analysis and monitoring of vine crops through remote sensing sensors and techniques. However, despite recent research efforts towards the detection and delineation at medium resolution scales the development and validation of efficient classification frameworks for operational vineyard detection in high resolution data and over large agricultural regions, still remains a challenge [3],[8].

In particular, the discrimination of vine varieties from remote sensing data has not concentrated much research efforts and has been mainly studied through the exploitation of hyperspectral data. The majority of studies aiming to discriminate between different vine varieties, employed CASI (Compact Airborne Spectrographic Imager) hyperspectral data and focused on a binary discrimination between two varieties [5],[6],[7].

In the present study, we employ very high resolution pan-sharpened multispectral satellite data towards the efficient vine parcel detection, vine rows extraction and vine variety discrimination. An object-based classification framework has been developed along with an adequate set of features and rules able to effectively identify vineyards in all datasets [1],[9]. The developed framework has been validated through various experiments for the discrimination of three and up to six different vine varieties.

2. DATA ACQUISITION

Data acquisition campaigns were conducted in four different viticulture regions in Greece mainland, all belonging to P.G.I. zones. The campaigns were scheduled during the véraison period, conducted in 2012 to 2014, from early July to early August. Very high resolution satellite imagery was acquired from the sensors of WorldView-2 (Panchromatic: 1 Band (450 - 800nm) - 0.5m spatial resolution, Multispectral:

8 Bands (400-1040nm) - 2m spatial resolution) and the Pléiades-1B (Panchromatic: 1 Band (480 - 830nm) - 0.5m spatial resolution, Multispectral: 4 Bands (480-950nm) - 2m spatial resolution), satellites.

Concurrently, field campaigns were conducted in all study areas collecting ground truth data for the precise location of parcels and varieties. Moreover, in situ reflectance measurements were performed using the GER 1500 (Spectra Vista Corporation, US) portable spectroradiometer, which provides spectra with 512 spectral bands distributed in the spectral region from 350nm to 1050nm with 3.2nm FWHM.

3. METHODOLOGY

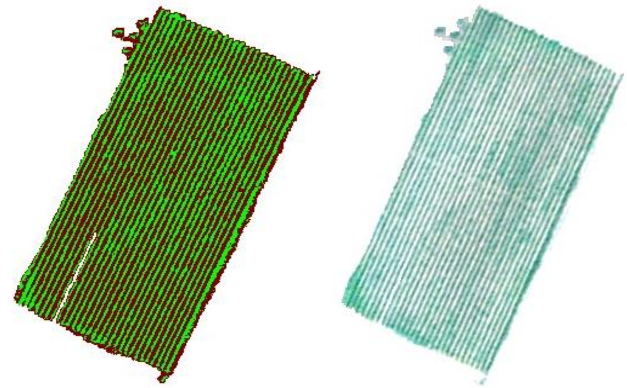
Before the main processing steps, radiometric and atmospheric corrections were performed on the satellite imagery towards the elimination of solar illumination, atmospheric and terrain effects. Atmospheric correction was conducted through Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH, Exelis Envi). The high resolution panchromatic data were then fused with the lower resolution multispectral data, through a pan-sharpening procedure, employing the High Pass Filter (HPF) resolution merge algorithm. Moreover, the observed radiance from the portable spectroradiometer was transformed to reflectance values based on the concurrent observations from a certified panel. The main methodology steps followed employing classification techniques, using Trimble's eCognition.

3.1. Vineyard detection

Before the classification, image objects were created on various scales using the multi-resolution segmentation algorithm. Then the various calculated objects were classified through a hierarchical classification procedure. In order to develop a generic classification solution through the knowledge-based scheme, the rules and features formed a single framework which applied in all datasets. In particular, the classifications were based on ten basic rules of spectral (*e.g.,* MSAVI index, mean NIR1) and texture features (*e.g.,* GLCM Dissimilarity, GLCM Std. Deviation). All images were classified using this rule set, allowing only slight modifications regarding mainly the fine tuning of the parameter values. The relationship between feature values and the degree of membership to a class was defined by membership functions, using fuzzy logic.

3.2. Vine canopy detection

A supervised classification using the standard nearest neighbour classifier was employed on the detected parcels in order to detect the canopy of each parcel and separate it from the soil in-between the vine rows. A fine segmentation was computed at first creating image objects of about 1-3



(a) (b)

Figure 1 – (a): The detected canopy of grapevine with green color and the detected soil with brown on a detected parcel and (b): the natural color composite of the same parcel.

pixels size and training samples for soil and vine canopy were manually collected by the expert. The features considered for the feature space of the classifier were mainly features of the category "To neighbor" (*e.g.,* Mean Diff. to Neighbors, Mean Diff. to Darker Neighbors) which describe the spectral relations between an image object and its neighbor image objects, in terms of mean layer intensity values. The use of these features was crucial as it exploited the alternation between vine rows and soil rows, in order to detect successfully the vine canopy (Fig. 1). The classifiers feature space also included some spectral features (*e.g.,* NDVI, band ratios).

3.3. Vine variety discrimination

Training samples for the different vine varieties were manually collected by the expert using reference and ground truth data, on the detected vine rows. The percentage of samples to objects varied from 1-3% per variety. A supervised classification took place based on the standard nearest neighbour classifier. Image objects were classified and a membership value (between zero and one) was assigned according to the distance of object feature space to its nearest neighbor. This distance was associated with a fuzzy dependency with the nearest sample of a given class.

Since the detection of different vine varieties was not a trivial task, an analysis on the relative reflectance data from the portable spectroradiometer, indicated a range of potential spectral features able to contribute effectively in the discrimination procedure. In particular, the features considered for the feature space of the classifier were spectral and mainly certain band ratios (*e.g.,* mean NIR1 / mean Blue ratio). In all study areas, more than ten vine varieties were studied and various combinations, from three up to six different varieties, were given as an input during this discrimination procedure.

(a) Detected Vineyards **(b) Ground Truth Data**

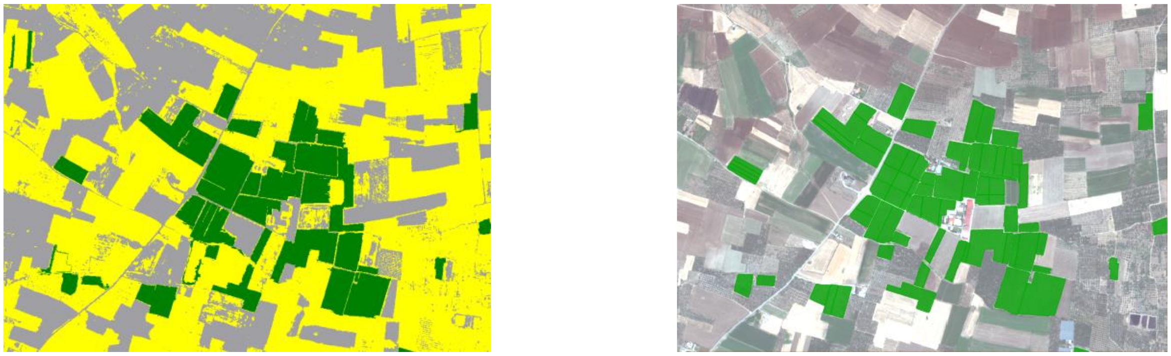


Figure 2 – (a): The detected vineyards (with green color) at the Megaplatanos study area and (b): the ground truth data with their exact position superimposed on the WV-2 image. High detection rates were reported regarding their detection completeness (96%) and correctness (93%).

4. EXPERIMENTAL RESULTS AND VALIDATION

A quantitative assessment was performed based on ground truth data which were formed after a comprehensive digitization procedure in all available datasets. The standard quantitative measures of Completeness, Correctness and Quality were employed for the evaluation of the vineyards' detection at pixel level. Regarding the vine variety classifications, the quantitative evaluation at pixel level was based on the calculated confusion matrix which includes the completeness rates for the detection of each variety. The success of the whole classification was expressed by the measure of Overall Accuracy (O.A.). The classification results were also evaluated at parcel level, through majority voting; the variety achieving the higher completeness percentage of parcel's ground truth pixels, labelled the parcel and then each parcel's classification was compared with the ground truth data. The latter can be considered closer to the actual application since in these study areas the different vine varieties are planted in a per parcel basis.

4.1. Vineyard detection

During the first processing step the developed classification procedure separates the image objects at three different classes *i.e.,* i) Vineyards, ii) other types of Vegetation and iii) Not-Vegetation.

In Fig. 2, experimental results after the application of the proposed methodology are shown for the Megaplatanos study area. In general, in all study areas only a small number of other-vegetation objects were confused and misclassified as vineyards. This was achieved due to the fact that the employed texture features managed to capture the dominating linear pattern of vine rows and to separate them from other vegetation objects with similar spectral behavior. Detecting vineyards on all pan-sharpened multispectral datasets resulted in overall to high completeness (>89%) and and correctness (>88%) rates.

4.2. Vine variety discrimination

After extracting the vine rows on the detected vine parcels we did numerous experiments towards the discrimination, by classifying between three and up to six different varieties per time and using different combinations.

In Fig. 3, parts of the classified images for the Naoussa and Amynteo study areas, when discriminating between four different varieties/clones, are presented. In both cases the correct class has been detected for the majority of the parcel's pixels and so the evaluation at parcel level results as completely successful. In all experiments the vine variety discrimination reported an overall classification accuracy of 59% at pixel level and of 97% at parcel level. In general the accuracy rates were getting lower as the number of varieties increased.

To sum up, based on all our experiments the discrimination of different varieties was a challenging task due to the similar spectral characteristics of the studied varieties. The performed evaluation on the results indicated that certain vine varieties like Merlot and Sauvignon Blanc, achieved high completeness rates on all classifications they took part, indicating relatively distinct spectral behavior among the other varieties. On the other hand pairs of other varieties like Tannat and Syrah, Riesling and Syrah, Cabernet Sauvignon and Ksinomavro, presented lower completeness rates as single classes, and high mixing rates between them, implying that they presented highly correlated spectral features. These conclusions were generally in accordance with the analysis of the spectroradiometer's reflectance hyperspectral data; Merlot and Sauvignon Blanc reflectance differed significantly from the others. In general, the vine variety discrimination at parcel level, indicated in most cases successful quantitative detection results (O.A.>85%).

(a) Syrah Parcel in Naoussa **(b) Montepulciano Parcel in Amynteo**

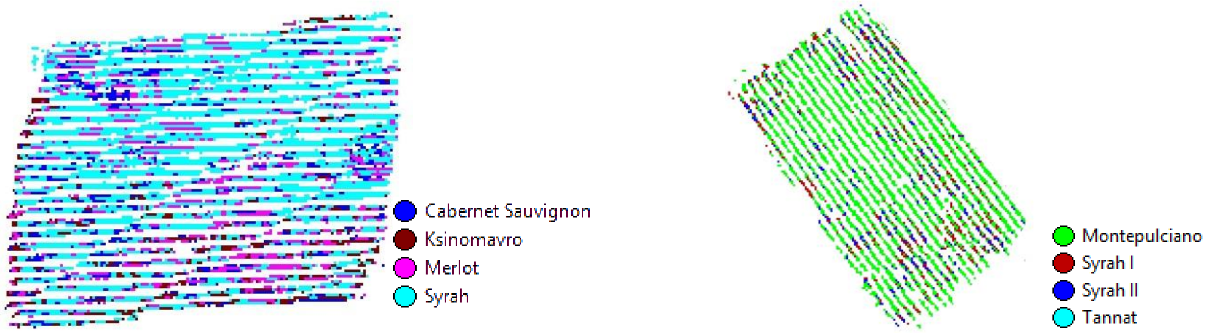


Figure 3 – (a): A detected Syrah parcel on the WV-2 imagery in Naoussa and (b): a detected Montepulciano parcel on the Pléiades-1B imagery in Amynteo. In both cases the goal of the classification procedure was to discriminate four different vine varieties/clones.

5. CONCLUSIONS

In this paper, an object-based detection and discrimination framework was developed and validated. Experimental results on all datasets indicated high detection completeness and correctness rates. In particular, vineyards were detected from very high resolution pan-sharpened satellite data (*i.e.,* WV-2 and Pléiades-1B). The same spectral and texture features along with the corresponding rules were employed in all datasets under an object-based image analysis framework. In all our experiments the discrimination of different varieties was a challenging task due to the similar spectral characteristics of the studied varieties. The vine variety discrimination at pixel level reported overall accuracies of about 60%. At parcel level the quantitative evaluation achieved in most datasets 100% successful results, concluding in an average O.A. of 97%. The successful validation of the developed detection and discrimination framework indicated that advanced remote sensing processing algorithms, high resolution multispectral pan-sharpened satellite imagery and concurrent field campaigns can form an effective tool for the semi-automated vineyard detection and variety discrimination.

6. ACKNOWLEDGEMENTS

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