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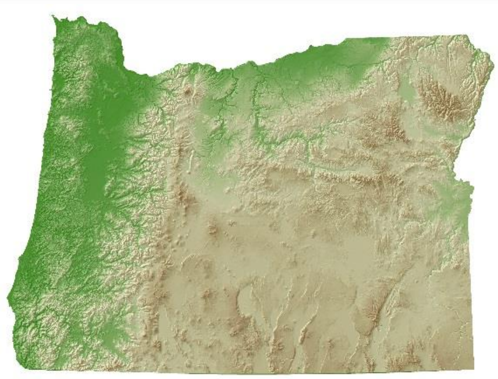

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VINEYARD YIELD ESTIMATION BY VINBOT ROBOT - PRELIMINARY RESULTS WITH THE WHITE VARIETY VIOSINHO

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Abstract

Nowadays it is recognized that vineyard yield estimation can bring several benefits to all the vine and wine industry and, consequently, there is a strong demand for fast and reliable yield estimation methods. Recently a strong effort has been made on developing machine vision tools to automatically estimate vineyard yields evolving several research teams worldwide. In this paper we aim to present preliminary results obtained in the frame of an European research project (VINBOT: "Autonomous cloud-computing vineyard robot to optimise yield management and wine quality") focus on yield estimation. A ground truth evaluation trial was set up in an experimental vineyard with the white variety Viosinho, trained on a vertical shoot positioning system and spur pruned. A sample of contiguous vines was labeled and submitted to a detailed assessment of vegetative and reproductive data to feed a viticulture data library. The vines were scanned during the ripening period of the 2015 season by the VINBOT sensor head composed with a set of sensors capable of capturing vineyard images and 3D data. Ground truth data was used to relate with images taken by the sensors and to test algorithms of image analysis. In this paper we present and discuss the relationships between actual and estimated yield computed using the surface occupied by the grape clusters in the images. Our preliminary results showed that, despite of a slight underestimation of the ground truth, caused mainly by cluster occlusion, when the canopy density allows visualization of most part of the clusters, the yield can be estimated by machine vision with a high fidelity. Further research is ongoing to test those devices and methodologies in other varieties and to improve the estimation accuracy.

Key words*: *grapevine, image analysis, precision viticulture, robot, Viosinho, Vinbot, yield estimation

1 INTRODUCTION

Vineyard yield is a variable that can display high variability either temporal, regional and local. Furthermore, within the same vineyard plot there is also variability between vines, between clusters of the same vine and between berries of the same cluster. The reasons for this variability are several being the most important ones the climate, soil, vine age, variety, biotic and abiotic stresses and the cultural practices used by the grower. Quantification of this variability is fundamental to the entire grape and wine production chain allowing several advantages that are highlighted as follows: planning cluster thinning needs (in order to prevent excessive production and consequent poor wine quality); planning and organization of the harvest (hand labor, equipment, etc.); planning cellar needs (scheduling grape intake; allocating tank space, purchasing tanks, barrels, oenological products, bottles and others); planning purchases and/or grape sales; establishment of grape prices and management of wine stocks; management of grape and wine market; programming investments and development of marketing strategies. This multiplicity of potential benefits makes the yield estimation one of the major current research topics in Viticulture.

The yield estimation of a vineyard can be obtained using several methods highlighting, among others, i) aeropalynological forecast models (Cunha et al. 1999); ii) methods based on the estimation of yield components (Clingellefer et al. 2001; Martins 2011; Lima 2014); iii) indirect methods based on remote sensing of the vegetation (Hall et al. 2002); iv) measurement of wire tension (Tarara and Bloom 2009) and v) image analysis (Dun and Martin 2004; Diago et al. 2012;. Nuske et al. 2014a; Herrero-Huerta et al. 2015; Ivorra et al. 2015). Among these methods the ones based on the estimation of yield components are the most used at a farm level (Clingeleffer et al. 2001). These methods allow the yield estimation at various phenological stages, from bud break to harvest, however are very time consuming and sometimes the estimation is not very accurate. Recently, several research teams worldwide have been developing tools based on various types of sensors installed on vehicles (autonomous or not), for vine phenotyping. An example of this research effort is the EU research project VINBOT (Autonomous cloud-computing vineyard robot to optimise yield management and wine quality) (http://www.vinbot.eu/) which aims at develop an all-terrain autonomous mobile robot with a set of sensors capable of capturing and analyzing vineyard images and 3D data by means of cloud computing applications, in order to obtain yield maps representing the spatial variability of the vineyard plots.

Agricultural robots have received significant attention during the past years. According to the International Federation of Robotics (2015), economic demands, shortages of skilled farm labor in agricultural regions, food and fiber requirements of a growing world population, and stringent standards will continue to drive the commercial need for agricultural robots. Some market reports (Agricultural Robots 2016) predict that agricultural robots will reach $16.8B by 2021 and $73.9B by 2024. The increasing importance of yield forecast has lead to automated solutions for the data acquisition and allowed the first service robotics applications in viticulture.

In this paper we aim to present some preliminary results obtained with the white variety Viosinho in the frame of the EU research project VINBOT ("Autonomous cloud-computing vineyard robot to optimise yield management and wine quality") focus on yield estimation.

2 MATERIALS AND METHODS

The VINBOT robot platform is based on a commercial off-the-shelf mobile robot Summit XL HL, that is able to carry up to 65 kg payload and consists of (Fig. 1):

-A robotic platform: durable, mobile, with ROS Indigo and Ubuntu 14.04;

-Color and NIR (Near Infra-Red) cameras to take high-precision images of the vine;

-3D range finders to navigate the field and to obtain the shape of the canopies;

-A small computer for basic computational functions and connected to a communication module;

-An optional RTK-DGPS high accuracy rover, optional base and associated communication devices;

-A cloud-based web application to process images or create 3D maps;

-User friendly HMI to define navigation and data acquisition missions.

VINBOT robot proposes a novel hybrid reactive/waypoint based navigation architecture, tested successfully in vineyard navigation. VINBOT makes use of a laser range finder and RGBD device to perform reactive row following and obstacle avoidance, while it can make use of other reactive behaviors or GPS waypoint navigation for changing from row to row or field to field, thus supporting different levels of automation.

Figure 1. View of the actual version of the Vinbot robot platform

For ground truth it was used an experimental vineyard of the "Instituto Superior de Agronomia", Lisbon (lat. 38.71 N; long. 9.18 W) planted in 2006 with a North-South oriented rows. The grapevines of the white variety Viosinho were grafted to 1103 Paulsen rootstock and spaced 1.0 m within and 2.5 m between rows. Vines were trained on a vertical shoot positioning with two pairs of movable wires and spur-pruned on a unilateral Royat Cordon system. All vines were uniformly pruned to 10-12 nodes per vine (5-6 two bud spurs). A row of 30 contiguous vines was labeled, subjected to a manual assessment of cluster number and total weight and simultaneously scanned by the VINBOT platform. Furthermore, all the clusters of five contiguous vines (98 clusters) were harvested separately, labeled, and then transported to the laboratory for detailed assessments. At the laboratory they were individually photographed with a compact camera, weighted and then processed in order to obtain the number, weight and volume of berries per bunch (data not shown). These cluster images were processed using an image analysis algorithm (ImageJ 1.48V) through which the projected area of each cluster was computed. In order to obtain an empirical relationship between the projected area of the clusters and the corresponding weight a linear regression analysis was computed. This ground truth database was used to the development and testing of image analysis algorithms and ultimately to validate the VINBOT yield estimations.

During the ripening period of 2015 season several image acquisition sessions were performed with the VINBOT platform which scanned both sides of the canopy. Data presented in this paper was obtained from the last session (August 24, 1 day before harvest), after a defoliation performed at cluster zone in order promote a better cluster detection by VINBOT cameras.

Regarding the machine vision procedures, in order to retrieve the regions where the clusters are located, and finally be able to compute accurate yield maps, we have used the approach for grape detection called

"Convolutional Neural Networks inside of Deep Learning Field" which is based on a structure of stacked multi-layer neural networks (Krizhevsky and Sutskever 2012). Once the clusters were recognized, the total area occupied by the clusters in the image was computed in pixels and then converted into actual cm^2. Finally, we have applied the formula presented in the plot of Fig. 3 which converts this area into kilograms.

3 RESULTS AND DISCUSSION

3.1 Yield and yield components variability

Figure 2 shows the variability among vines on number of clusters, cluster weight and yield along a vineyard row. The number of clusters per vine presented an average value of 18.8 with a coefficient of variation (CV) of 21.1%, yielding the highest value on the vine # 5 (31 clusters) and the lowest one on vine #18 (12 clusters) (Fig. 1A). The yield per vine showed an average of 4.7 kg with a CV of 28.9% yielding the highest production in vine # 5 (8.2 kg) and the lowest one on vine #22 (2.4 kg) (Fig. 1B). Average weight per cluster showed an average of 251.9 g with a CV of 22.6% yielding the highest value on the vine #12 (359 g) and the lowest one on the vine # 22 (126 g) (Fig. 1C). As the average cluster weight was obtained per vine (dividing yield by cluster number) it do not reflect the actual variability of the individual cluster weight. Indeed, detailed individual cluster weight data obtained on the 5 vines sampled for detailed measurements show that the actual cluster weight has a higher variability: CV = 39.2% with the highest value of 460.6 g and the lowest one of 27.6 g.

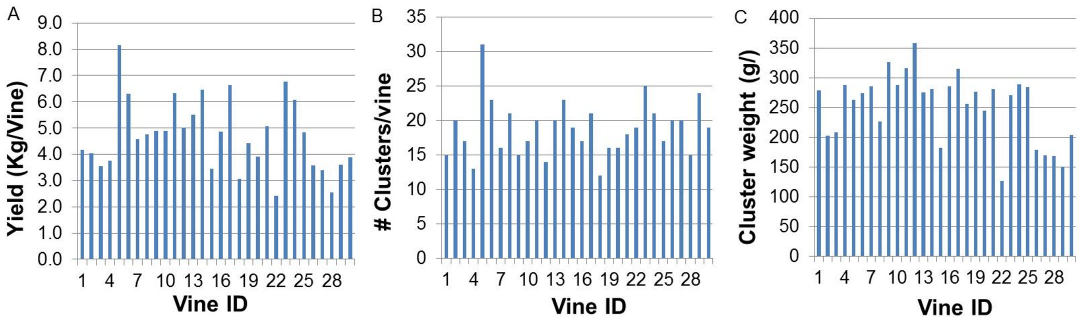

Figure 2. Yield and yield components variability along a vineyard row (30 contiguous vines), variety Viosinho, Tapada da Ajuda, Lisbon, 2015. A: Cluster number per vine; B: yield per vine; C: average cluster weight per vine.

3.2 Yield estimation by VINBOT platform

Using image analysis algorithms the number of pixels relating to the visible clusters was computed. The number of pixels was then scaled and converted to kg of grape based on an equation obtained from the relationship between cluster area and weight obtained in the laboratory from a sample of 98 clusters; Fig. 3). As can be seen from the linear regression analysis presented in figure 2, the projected area of the clusters was able to explain *ca* 80% of the cluster weight variability, indicating that it can be used as an accurate estimator for the weight of the clusters.

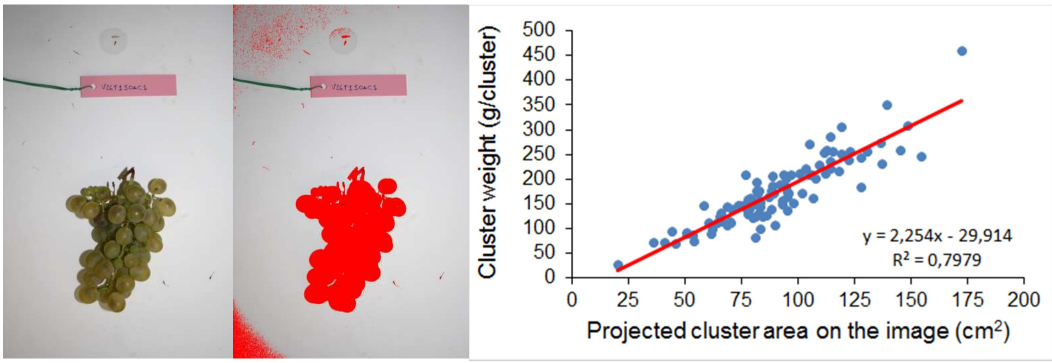

Figure 3. Example of image processing using the software *ImageJ* for estimation of projected cluster area (left) and linear regression analysis between the projected cluster area (independent variable) and cluster weight (dependent variable), variety Viosinho, 2015; n=98 (right).

Figure 4 shows the comparison between actual and estimated yield using image analysis algorithms based on the projected area of the visible clusters detected by VINBOT cameras. Despite an average underestimation of 0.29 kg per vine (ca 5.7%) in general a satisfactory agreement between observed and estimated yield was obtained (Fig. 4). The underestimation may be explained by the occlusion of some clusters by other clusters. This occlusion, which depends on cluster number per vine and on cluster size, constitutes a major problem of this approach, as noted by Nuske et al. (2014b) who proposed several alternatives based on modeling and calibration of occlusion ratio to overcome the problem. However, as there are still some vines showing big differences between actual and estimated yield, we are now analyzing in-depth those discrepancies in order to find other reasons for the differences and improve the prediction ability.

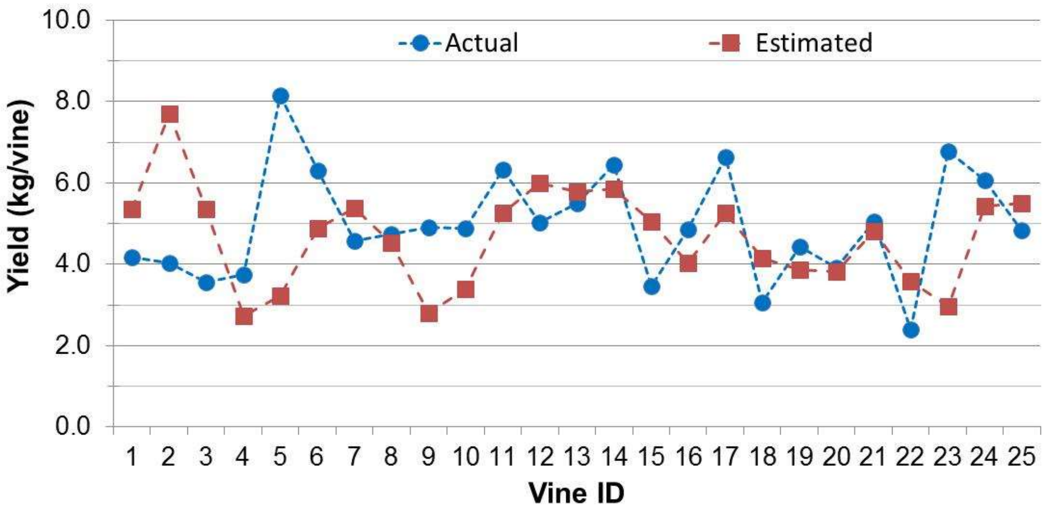

Figure 4. Comparison between actual and estimated yield by the Vinbot platform, along a row of the vineyard (n=25 vines), variety Viosinho, 2015. Mean Absolute % Error: 27.8; RMSE: 1.8.

4 CONCLUSIONS

Preliminary results show that, despite a slight underestimation induced by some cluster occlusion, when the canopy density allows visualization of most part of the clusters, the yield can be estimated with a small error with the VINBOT platform. Research is ongoing in order to test the platform and machine vision algorithms in other varieties and vineyard plots and to solve the problem of occluded clusters. Special attention is being paid to overcome the difficulties related to the hidden clusters by vegetation.

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