GRAPEVINE YIELD PREDICTION USING IMAGE ANALYSIS - IMPROVING THE ESTIMATION OF NON-VISIBLE BUNCHES

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ABSTRACT

Yield forecast is an issue of utmost importance for the entire grape and wine sectors. There are several methods for vineyard yield estimation. The ones based on estimating yield components are the most commonly used in commercial vineyards. Those methods are generally destructive and very labor intensive and can provide inaccurate results as they are based on the assessment of a small sample of bunches. Recently, several attempts have been made to apply image analysis technologies for bunch and/or berries recognition in digital images. Nonetheless, the effectiveness of image analysis in predicting yield is strongly dependent of grape bunch visibility, which is dependent on canopy density at fruiting zone and on bunch number, density and dimensions. In this work data on bunch occlusion obtained in a field experiment is presented. This work is set-up in the frame of a research project aimed at the development of an unmanned ground vehicle to scout vineyards for non-intrusive estimation of canopy features and grape yield. The objective is to evaluate the use of explanatory variables to estimate the fraction of non-visible bunches (bunches occluded by leaves). In the future, this estimation can potentially improve the accuracy of a computer vision algorithm used by the robot to estimate total yield.

In two vineyard plots with Encruzado (white) and Syrah (red) varieties, several canopy segments of 1 meter length were photographed with a RGB camera and a blue background, close to harvest date. Out of these images, canopy gaps (porosity) and bunches' region of interest (ROI) files were computed in order to estimate the corresponding projected area. Vines were then defoliated at fruiting zone, in two steps and new images were obtained before each step.

Overall the area of bunches occluded by leaves achieved mean values between 67% and 73%, with Syrah presenting the larger variation. A polynomial regression was fitted between canopy porosity (independent variable) and percentage of bunches not occluded by leaves which showed significant R^2 values of 0.83 and 0.82 for the Encruzado and Syrah varieties, respectively.

Our results show that the fraction of non-visible bunches can be estimated indirectly using canopy porosity as explanatory variable, a trait that can be automatically obtained in the future using a laser range finder deployed on the mobile platform.

Keywords: Precision viticulture, bunch occlusion, image analysis, robot, yield estimation

1. INTRODUCTION

Accurate yield estimation is extremely useful for the management of any crop. In viticulture this information can help vineyard managers in several aspects such as defining staff and machinery needed for harvest, future fertilization planning or anticipation of cellar needs (e.g. allocating tank space for wine making). If done early enough, yield forecasting can bring advantages towards planning bunch thinning needs (in order to prevent excessive yield and consequent poor wine quality), planning purchases and/or grape sales, establishing grape prices and managing wine stocks and grape and wine market, programming investments and developing marketing strategies (Dunn and Martin, 2004). However, yield estimations early in the season carry higher risk of lower accuracy due to unpredictable negative effects of biotic and abiotic factors, which may affect the final number and size of berries. These factors induce a high yield variability, both spatial and seasonal (Bramley and Hamilton, 2004; Victorino *et al.*, 2017) and therefore, yield predictions need to be considered for every season.

Traditional methods for yield estimation are based on counting sampled yield components which can be done all along the growing cycle. The veraison stage is one of the most used phenological stages to apply these methods as it is early enough for crop and winery managers to adapt their plans if needed, while also close enough to harvest to not jeopardize the estimation's accuracy. Estimations based on manual counting of yield components are simple enough to be accessible to anyone, and are still the most common practice today. However these methods are very labor-intensive and have low accuracy due to the difficulties related to sampling a large amount of vineyard area (Dunn and Martin, 2004).

To overcome the above-mentioned limitations, several methods have been developed. While some of them remain at a research level (Tarara *et al.*, 2014; Fraga and Santos, 2017) others are already in use by the industry, as is the case of the aeropalynological forecast models (Besselat, 1987; Cunha *et al.*, 2016). However, the aeropalynological methods are used mainly at a regional scale and are not recommended to be used by an individual winegrower, as the pollen grains transported by the wind can come from a highly unpredictable range of places and distances, not being site specific.

Recently, a big research effort has been done regarding the use of sensor-based technologies to address the overall yield estimation challenge. Nevertheless, so far, no commercial imaging-systems are available for grapevine yield estimation (Taylor *et al.*, 2018) but many recent new approaches are being developed.

Sensor-based methodologies encompass several challenges, being image data analysis one of the main ones. With the advancement of machine learning and its recent migration to agriculture applied technologies, new image processing algorithms have been developed bringing the possibility of analyzing great amounts of images in a short period of time. With such technology, pictures taken from the vineyard with, for example, a mobile platform, can today be automatically inspected, a task that would otherwise take many hours if done by a person.

One of the first attempts to use image analysis for yield estimation in viticulture was done by Dunn and Martin (2004). Since then, many new approaches that included machine learning algorithms were developed and are thoroughly reviewed up until 2017 by Seng *et al.* (2018). However, being such a trending technology, several recent works have been developed in the meantime for vineyard field conditions using machine learning. Such algorithms attempt to automatically extract information regarding a desired yield component in the collected image. This technology serves as an upgraded way to count yield components for yield estimation in automatic systems that collect extensive amounts of image data.

Neural networks (a particular type of machine learning algorithm) have been used for flower detection by Liu *et al.* (2018), for bunch detection by Milella *et al.* (2019), and for single berry detection by Aquino *et al.* (2018). Other models have been successfully used for this purpose, such as Boolean models (Millan *et al.*, 2018) and Random Forest Classifiers (Riggio *et al.,* 2018) for single

berry detection, as well as Support Vector Machines (Pérez-Zavala *et al.*, 2018) for bunch segmentation.
In several of these cases, images were collected using an on-the-go platform, some at night time with artificial lighting. This type of lighting prevents variability on light conditions, caused by different sunshine intensity and orientation, while also removes background noise from vines behind the targeted ones.
All of the previous algorithms had successful results at detecting yield components in grapevine images. However all of them are dependent of leaf removal, as vegetation in normal conditions covers a great percentage of the grape bunches (Nuske *et al.*, 2014). However, as leaf removal is not a generalized practice, yield estimation methods should rely on non-manipulated canopies, where part of the grape bunches are occluded by leaves. The fraction of bunches occluded by leaves is dependent of canopy porosity (fraction of gaps in the fruiting zone; Smart and Robinson, 1991). Compared to a dense canopy, a sparse one will have more gaps enabling more bunch visibility. Canopy porosity is most commonly measured using the *Point Quadrat* method, adapted to grapevines by Smart (1987). However, more recently it has been estimated using image analysis (De Bei *et al.*, 2016; Diago *et al.*, 2016), which would be most adequate when using sensor-based technology for yield estimation.
The present work explores the possibility of using grapevine canopy porosity as an explanatory variable to estimate grape bunches occluded by leaves, to be applied on yield estimation methods based on image analysis. Preliminary results from the 2018 season are shown.

2. MATERIAL AND METHODS

2.1. Site description and climatic conditions

The experiment was carried out during the 2018 season in two adult experimental vineyards plots located at Tapada da Ajuda, Lisboa (38°42'24,61" N; 9°11’05,53" W). In the first vineyard plot, grapevines of the white variety Encruzado were planted in 2006 with a spacing of 2.5m between and 1.0m within row, on a N-S row orientation. The vines are spur pruned on a unilateral Royat cordon and trained to a vertical shoot positioning trellis system with two pairs of movable wires. The second vineyard plot, grapevines of the red variety *Syrah*, were planted in 1998 with a plant density of 3,333 plants/ha (spacing of 2.5m between and 1.2m in row) and a N-S row orientation. The vines are spur pruned on a bilateral Royat cordon and trained to a vertical shoot positioning trellis system with two pairs of movable wires.

2.2. Image acquisition

Lateral grapevine field images were captured with a commercial camera (Nikon D5200) at the end of August 2018 when plants reached the BBCH phenological stage 85 (Lorenz *et al.*, 1995). The camera, configured in auto mode, was mounted on a tripod located approximately 2 m away from the row axis and 1 m above the ground. Images were collected with a blue background in a total of six 1 m segments (corresponding approximately to one vine) at three to five manual defoliation steps (Fig. 1). A total of 30 and 21 images were analyzed for *Encruzado* and *Syrah*, respectively.
Images of non-defoliated vines were collected. Out of these images, canopy gaps and bunches’ *region of interest* (ROI) files were computed in order to estimate the projected area of these parameters. Grapevines were then defoliated, at fruiting zone, in two steps in order to create different canopy porosity levels. First, half the leaves were taken off (half defoliation) then, the remaining ones (full defoliation). Between each defoliation moment new images were obtained using the same methodology described above. Images were collected close to 11:00 a.m. from the eastern side of the canopy.

Figure 1. Images collected between defoliation steps on the variety *Encruzado*. A) non-defoliated vine. B) half-defoliated vine. C) fully-defoliated vine.

2.3. Image analysis & estimation of parameters

Images were analyzed using the ImageJ software (v1.52e, National Institutes of Health, EUA). The original images were cropped to include only the fruiting zone, which reaches from the cordon up to approximately 40 cm above the cordon. For each defoliation step, grape bunch projected area was outlined in order to estimate the corresponding number of pixels.

The percentage of visible bunches (% VB) was then calculated (Eq. 1) by dividing the visible bunch pixels (VBpx) by the total bunch pixels (TBpx), computed from the fully-defoliated vine.

$$\%\mathrm{VB} = \frac{\mathrm{VBpx}}{\mathrm{TBpx}} \times 100 \qquad \text{(Eq. 1)}$$

In the same image, canopy gaps were classified with the blue background (Fig. 1) using the Hue-Saturation-Brightness (HSB) representation of the image. The Brightness channel was ignored to maintain uniform levels of brightness across all images. The Hue and Saturation histograms were tuned in order to classify only the blue background.

The percentage of gaps (porosity; % Por) was finally calculated as the number of blue pixels classified (Gaps), divided by the total number of pixels in the image (Totalpx; Eq. 2).

$$\%\mathrm{Por} = \frac{\mathrm{Gaps}}{\mathrm{Totalpx}} \times 100 \qquad \text{(Eq. 2)}$$

A polynomial regression was then fitted using %Por as independent variable to estimate %VB. All data analysis was performed using SAS®.

3. Results & discussion

Both varieties present a similar number of bunches but large differences on bunch weight and yield with Syrah showing the lower values (Table 1).

Table 1. Summary results for yield and yield components, porosity and bunch occlusion by leaves, accessed one week before the harvest, per variety. Mean ± standard error. Data for non-defoliated vines.

Variables	*Encruzado*	*Syrah*
Number of bunches (bunches/m)	22.0 ± 1.4	20.0 ± 0.6
Average bunch weight (g)	200.3 ± 16.4	119.7 ± 8.1
Yield (kg/m)	4.4 ± 0.4	1.9 ± 0.3
Yield (ton/ha)	17.7 ± 1.5	6.3 ± 1.1
Porosity (%)	22.5 ± 3.3	16.8 ± 2.0
Bunches occluded by leaves (%)	66.7 ± 4.5	72.8 ± 6.2

In non-defoliated vines, leaves occluded up to 66.7% and 72.8% for *Encruzado* and *Syrah* varieties, respectively, showing the importance of this feature regarding bunch visibility (Table 1).

A high variation of this occlusion appears to be explained by canopy porosity as it was previously proposed for this work, showing significant relationship (R^2=0.78) in a simple linear regression analysis, for the *Encruzado* variety. To improve this relationship a third order polynomial regression was fitted with a $R^2 = 0.83$ (eq. 5; Fig. 4).

$$y = -0.0016x^3 + 0.1503x^2 - 2.2786x + 38.475 \qquad \text{(eq. 5)}$$

As for the *Syrah* variety, a simple linear regression analysis also showed significant results (R^2=0.80) which was again improved by a polynomial regression of third order that yielded a $R^2 = 0.82$ (eq. 6).

$$y = -0.0009x^3 + 0.0805x^2 - 0.3281x + 20.071 \qquad \text{(eq. 6)}$$

Porosity never reaches values above 80% even after full defoliation, because other organs remain present (mostly branches and bunches).

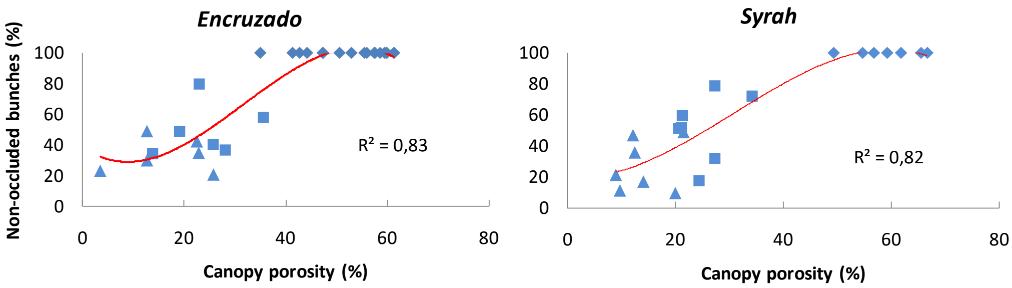

Figure 2. Polynomial regressions between non-occluded bunches and canopy porosity for the varieties *Encruzado* (n=30) and *Syrah* (n=21). Triangles, squares and diamonds represent vines that are non-defoliated, half-defoliated and fully-defoliated, respectively.

Results indicate that it is possible to estimate yield on non-defoliated vines based on canopy porosity. This information goes against what was previously stated by Aquino *et al.* (2018) claiming that the randomness of fruit exposure makes accurate yield predictions unsuitable.

4. Conclusions

A suitable way to explore yield estimation based on image analysis without recurring to invasive methods such as defoliation is explored in this work. It was firstly observed that leaves were the main vine organ occluding grape bunches and that canopy porosity has an impact on bunch exposure.

The significant relationships obtained for both varieties between canopy porosity and % exposed bunches indicates that canopy porosity is a reliable predictor for the fraction of visible bunches detected on lateral vine images taken in field conditions. Therefore, by segmenting visible bunch pixels and estimating canopy porosity it might be possible to indirectly estimate the portion of non-visible bunches.

Further research is ongoing focusing on the increase of the number of seasons and vines analyzed. Additionally, different levels of manipulated porosity are being explored on separated sets of vines in order to simulate a more broaden spectrum of field conditions. Furthermore, it was observed that a significant part of bunch occlusion is caused by neighboring bunches, a factor that is currently also being evaluated. Finally, work is ongoing to explore the prediction of occluded bunches and its viability for yield estimation models.

References

Aquino, A. *et al.* (2018) 'Automated early yield prediction in vineyards from on-the-go image acquisition', *Computers and Electronics in Agriculture*. doi: 10.1016/j.compag.2017.11.026.

De Bei, R. *et al.* (2016) 'Viticanopy: A free computer app to estimate canopy vigor and porosity for grapevine', *Sensors (Switzerland)*. doi: 10.3390/s16040585.

Besselat, B. (1987) 'Les prévisions de récolte en viticulture', 1985(Tableau 1), pp. 1–12.

Bramley, R. G. V and Hamilton, R. P. (2004) 'Understanding variability in winegrape production systems 2. Within vineyard variation in quality over several vintages', *Australian Journal Of Grape And Wine Research*, 10(1), pp. 32–45. doi: 10.1111/j.1755-0238.2004.tb00006.x.

Cunha, M., Ribeiro, H. and Abreu, I. (2016) 'Pollen-based predictive modelling of wine production: Application to an arid region', *European Journal of Agronomy*. Elsevier B.V., 73, pp. 42–54. doi: 10.1016/j.eja.2015.10.008.

Diago, M. P. *et al.* (2016) 'Assessment of vineyard canopy porosity using machine vision', *American Journal of Enology and Viticulture*. doi: 10.5344/ajev.2015.15037.

Dunn, G. M. and Martin, S. R. (2004) 'Yield prediction from digital image analysis: A technique with potential for vineyard assessments prior to harvest', *Australian Journal of Grape and Wine Research*. doi: 10.1111/j.1755-0238.2004.tb00022.x.

Fraga, H. and Santos, J. A. (2017) 'Daily prediction of seasonal grapevine production in the Douro wine region based on favourable meteorological conditions', *Australian Journal of Grape and Wine Research*. doi: 10.1111/ajgw.12278.

Liu, S. *et al.* (2018) 'A robust automated flower estimation system for grape vines', *Biosystems Engineering*. doi: 10.1016/j.biosystemseng.2018.05.009.

Lorenz, D. H. *et al.* (1995) 'Growth Stages of the Grapevine: Phenological growth stages of the grapevine (Vitis vinifera L. ssp. vinifera)—Codes and descriptions according to the extended BBCH scale', *Australian Journal of Grape and Wine Research*, 1(2), pp. 100–103. doi: 10.1111/j.1755-0238.1995.tb00085.x.

Milella, A. *et al.* (2019) 'In-field high throughput grapevine phenotyping with a consumer-grade depth camera', *Computers and Electronics in Agriculture*. Elsevier, 156(November 2018), pp. 293–306. doi: 10.1016/j.compag.2018.11.026.

Millan, B. *et al.* (2018) 'On-the-Go Grapevine Yield Estimation Using Image Analysis and Boolean Model'. doi: 10.1155/2018/9634752.

Nuske, S. *et al.* (2014) 'Automated visual yield estimation in vineyards', in *Journal of Field Robotics*. doi: 10.1002/rob.21541.

Pérez-Zavala, R. *et al.* (2018) 'A pattern recognition strategy for visual grape bunch detection in vineyards', *Computers and Electronics in Agriculture*. Elsevier, 151(September 2017), pp. 136–149. doi: 10.1016/j.compag.2018.05.019.

Riggio, G., Fantuzzi, C. and Secchi, C. (2018) 'A Low-Cost Navigation Strategy for Yield Estimation in Vineyards', *2018 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, pp. 2200–2205. doi: 10.1109/ICRA.2018.8462839.

Seng, K. P. *et al.* (2018) 'Computer vision and machine learning for viticulture technology', *IEEE Access*. IEEE, 6, pp. 67494–67510. doi: 10.1109/ACCESS.2018.2875862.

Smart, R. E. (1987) 'Influence of light on composition and quality of grapes', *Acta Horticulturae*, 206, pp. 37–48.

Smart, R.E. and Robinson, M. (1991) 'Sunlight into Wine: A Handbook for Winegrape Canopy Management'. Winetitles, Adelaide.

Tarara, J. M. *et al.* (2014) 'Use of cordon wire tension for static and dynamic prediction of grapevine yield', *American Journal of Enology and Viticulture*, 65(4), pp. 443–452. doi: 10.5344/ajev.2014.14021.

Taylor, J. A. *et al.* (2018) 'Considerations on spatial crop load mapping', *Australian Journal of Grape and Wine Research*. doi: 10.1111/ajgw.12378.

Victorino, G., Braga, R. and Lopes, C. M. (2017) 'The effect of topography on the spatial variability of grapevine vegetative and reproductive components', pp. 510–516.