APPLICATIONS OF MACHINE VISION FOR GRAPEVINE PHENOTYPING

APPLICATIONS DE LA VISION ARTIFICIELLE POUR LE PHÉNOTYPAGE DE LA VIGNE

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Abstract
Computer vision systems are powerful tools to assess canopy status, fruit grading, and yield in agriculture. This work shows the application of machine vision techniques for grapevine phenotyping under laboratory and field conditions. The first approach aimed at determining automatically the number of flowers per inflorescence using a low cost camera under field conditions. Strong and significant relationships, with R^2 above 0.8 in Tempranillo, Graciano and Carignan cultivars were observed between actual and automated estimation of inflorescence flower numbers. The second approach aimed at analysing cluster morphology using image analysis under laboratory conditions. Berry weight, berry number per cluster and cluster weight were estimated using several algorithms of image processing. The best results (R^2 between 0.69 and 0.95 in berry detection and between 0.65 and 0.97 in cluster weight estimation) were achieved using the Canny algorithm. The model's capability based on image analysis to predict berry weight was R^2=0.84. The third approach aimed at working outdoors, developing in-field systems capable of assessing the leaf area and yield of the vineyard by acquisition and processing of digital images. Our algorithms allowed the total leaf area (R^2=0.81; p<0.001) and yield (R^2=0.73; p=0.002) per vine to be estimated. In conclusion, computer vision techniques can be applied in viticulture for plant phenotyping and vineyard monitoring. A large set of samples can be automatically measured, saving time and providing more objective and precise information.

Keywords : *computer vision, image analysis, cluster components, grapevine, vineyard monitoring*

Résumé
Les systèmes de vision par ordinateur sont de puissants outils, qui pour l'agriculture permettent d'évaluer l'état de la canopée, , la qualité des fruits et le rendement. Ce travail montre l'application de la vision artificielle appliquée au phénotypage de la vigne en laboratoire et sur le terrain. La première approche vise à déterminer le nombre de fleurs par inflorescence automatiquement en situation terrain, à l'aide d'une caméra à faible coût. Les corrélations entre les valeurs réelles et l'estimation automatisée du nombre de fleurs d'une inflorescence sont significatives avec un R^2 supérieur à 0.80 pour les cépages Tempranillo, Graciano et Carignan. La deuxième approche est destinée à l'analyse morphologique du fruit grâce à la vision articifielle en laboratoire. Le poids de la baie, ainsi que le nombre de baies par grappe et le poids de la grappe ont été estimés en utilisant plusieurs algorithmes de traitement d'images. Les meilleurs résultats (R^2 entre 0.69 et 0.95 pour la détection de la baie et entre 0.65 et 0.97 pour l'estimation du poids de la grappe) ont été obtenus en utilisant l'algorithme Canny. Le modèle basée sur la vision artificielle par permet de prédire le poids de la baie était de R^2=0.84 . La troisième approche est destinée à travailler à l'extérieur, pour développer des systèmes de terrain capables d'évaluer la surface foliaire et le rendement du vignoble par acquisition et traitement d'images. Les algorithmes développés permettent d'évaluer la surface foliaire totale (R^2=0.81; p<0.001) et le rendement (R^2=0.73; p=0.002). En conclusion, la vision artificielle peut être appliquée dans le domaine de la viticulture pour le phénotypage du vignoble et son monitoring. Un grand nombre d'échantillons peuvent être automatiquement mesurées, offrant un gain de temps et des informations précises et plus objectives.

Mots-clés : vision artificielle , analyse d'images, compacité de la grappe, vigne, moniting du vignoble

1. Introduction

The development and application of innovative techniques, such as artificial vision and image analysis, aimed at objectively monitoring the vineyard is a key issue in viticulture research in order to improve grape-growing sustainability as well as grape and wine quality.

Cluster weight and morphology are mainly determined by flowering and fruit set. These two physiological processes define the number of berries per cluster, which, together with berry volume, influence cluster architecture and compactness (looser or tighter clusters), considered as indicators of grape and wine quality (Matthews and Nuzzo, 2007). A count of the flower number per inflorescence is essential for accurate assessment of fruit set, but doing it manually is time consuming and labour demanding, so an automated method will be very advantageous. Computer vision could be also used for assessing cluster morphology and berry weight as a rapid and accurate method. Moreover, canopy features including leaf area, canopy porosity and fruit exposure are related to fruit microclimate, fruit health status and grape composition. Image analysis has been applied to grapevine canopy images taken in the vineyard for assessing yield (Dunn and Martin, 2004) and the impact of early defoliation (Tardaguila et al., 2010) on the main canopy features.

This work presents three approaches of machine vision in viticulture :

1) at inflorescence level, to estimate the flower number per inflorescence under field conditions,
2) at a cluster level, to estimate berry number per cluster and cluster weight, and
3) at canopy level, to assess two key parameters such as leaf area and yield per vine under field conditions.

2. Materials and Methods

a) Estimation of Flower Number per Inflorescence under field conditions

Images of the inflorescences of *Vitis vinifera* L. cvs Tempranillo, Graciano and Carignan were acquired at pre-flowering, when inflorescences are swelling, and flowers closely pressed together. For each cultivar, 30 inflorescences were photographed with a digital camera (Canon model Ixus 850 IS, Tokyo, Japan) under field conditions. For each individual inflorescence a single image was taken. To make sure a high colour contrast that eased the segmentation process of inflorescences, a uniform black background was used.

Images were processed using a specific image analysis algorithm developed in Matlab™ (Mathworks, USA) that involved three stages: (i) image pre-processing: automated definition of a region of interest (ROI) of the inflorescence removing the background influence (ii) flower counting: This stage was focused on detecting and counting the number of bright spots caused by direct reflection of the light on the spherical surface of objects in the image which usually corresponded to the presence of flower and it is based on the computation of the extended-maxima transform. (iii) image postprocessing: selected bright spots included other material than flowers, so several filtering processes were defined based on a) region size and b) distance between bright spots (Diago et al., 2014a). In order to validate the image analysis algorithms, the actual flower number per inflorescence was determined manually after image acquisition by individually detaching the flowers from the rachis and also by manually counting the flowers on printed images.

b) Estimation of Cluster Weight and Berry Number per Cluster

Cluster samples of seven different red varieties of *Vitis vinifera* L. (10 clusters per variety): Carignan, Grenache, Monastrell, Bobal, Cabernet Sauvignon, Tempranillo and Merlot were photographed in an inspection chamber at the laboratory. After image acquisition, clusters were weighed and berries in each cluster were manually counted.

The images were acquired using a digital still camera (Canon, EOS 550D, USA) placed inside of a squared inspection chamber with controlled illumination. In order to facilitate the image segmentation, a uniform orange background was used. During the image acquisition, clusters were hanging from a clamp to not distort their shape (Diago et al., 2014b). A total of 280 images were acquired, as 10 clusters per variety were studied and four views per cluster were photographed by rotating 90º the cluster from one image to another. The image processing was aimed at detecting each berry in the cluster automatically. In a first step, the cluster was discriminated from the background by thresholding. The next step consisted on delimitating the contour of the berry based on edge analysis using the Canny algorithm (Canny 1986), looking for local maxima of the gradient in the edge. Once the contours of the berries were extracted, the Hough transform was used to find those contours forming circles. The output of the algorithm yielded an array containing the coordinates of the centres and the radii of the circles detected. To avoid redundancy a filtering on the detected centres was conducted (Diago et al., 2014b).

All clusters were manually destemmed and all the berries counted and weighed. Two regression models were fitted between :
1) the total berries estimated using the four images per cluster, and the actual number of berries in the cluster counted manually, and
2) the number and size of the berries and the weight of the cluster. To properly validate the models, the regression models obtained were used to predict the size and weight values of the validation set.

c) Analysis of the yield and leaf area under field conditions

The experiments were conducted in 2010 in a commercial dry-farmed cv. Tempranillo (*Vitis vinifera* L.) vineyard located in La Rioja, Spain. Ten vines were randomly chosen, and each of them was successively defoliated and the cluster thinned in three steps, and after each step, the leaf area and/or fruit removed were also recorded. All main and lateral leaves per vine were separately removed and total leaf area was determined using a leaf area meter (LI-3100C, Li-Cor, USA) in the laboratory. Moreover, all clusters per tagged vine were weighed and yield per vine was determined. The labelled vines were photographed at 1 meter distance from the fruiting zone using a digital camera (Pentax model K200D, Tokio, Japan) mounted on a tripod. A white screen was placed behind the canopy to avoid confounding effects due to background vegetation. The images were analysed using a specific image analysis algorithm developed in Matlab™ (Mathworks, USA). The algorithm worked with the user defined pixels for every class as a starting point for a classification algorithm based on Mahalanobis distance (Diago et al., 2012). Four different classes were established: clusters, green leaves, yellow-wilted leaves and canopy porosity. The program was then used to automatically count the total number of pixels in each class.

3. Results and Discussion

a) Estimation of Flower Number per Inflorescence

The effectiveness of the implemented algorithm was tested against the destructive manual counting of the actual flower number per inflorescence, and also compared to the manual estimation from photo prints. Automatic counting using the developed method allowed the flowers to be distinguished from other parts of the inflorescence and also from the background. The relationship between the number of flowers detected both manually and automatically from the images, and the actual flower number per inflorescence, determined by destructive removal and counting are reported for Graciano (Figure 1a), Carignan (Figure 1b), Tempranillo (Figure 1c) and all three cultivars together (Figure 1d).

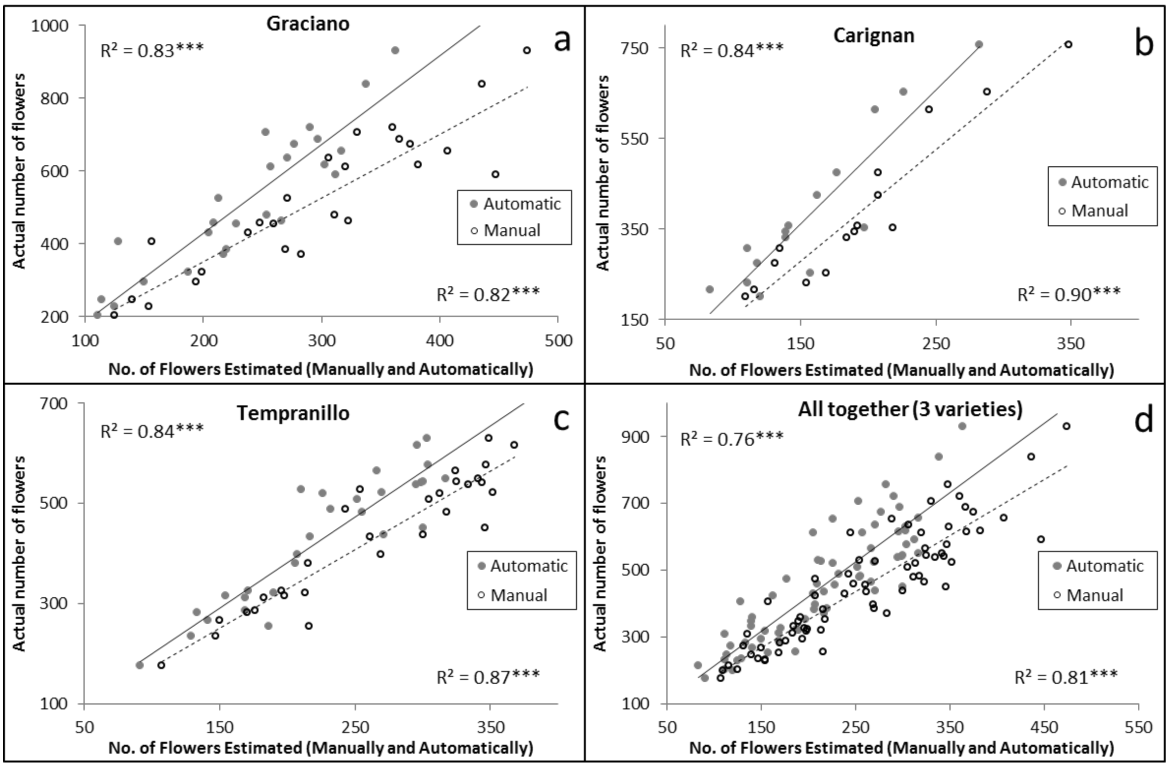

Figure 1. *(**a**) Relationships between the actual number of flowers per inflorescence and the number of flowers detected both manual and automatically from digital images for (**a**) Graciano, (**b**) Carignan, (**c**) Tempranillo and (**d**) these three varieties together. The solid and the dashed lines represent a linear fit of automatically, and manually (from photo prints) estimated flowers respectively (*** significant at p<0.001).*

Figure 1. **(a)** Relations entre le nombre de fleurs observées par inflorescence et le nombre de fleurs détectées manuellement et automatiquement à partir d'images numériques, pour les cépages (**a**) Graciano, (**b**) Carignan, (**c**) Tempranillo, et (**d**) les trois cépages ensemble. Les lignes continues et pointillés représentent respectivement l'ajustement obtenu respectivement pour l'estimation du nombre de fleurs automatiquement et manuellement (*** significatif pour p<0.001).

For these three cultivars, considering each one individually, the determination coefficient (R^2) of the relationships between the number of flowers estimated either manual or automatically with the developed method, to actual flower number per inflorescence, was always higher than 0.80 (P<0.001). No strong differences in R^2 values were found between manual and automated flower estimation. However, R^2 diminished to 0.76 when the three varieties were considered together in the automated mode.

b) Estimation of Cluster Weight and Berry Number per Cluster

Table 1 shows the mean R^2 (p<0.001) value for estimating berry number per cluster for all varieties. The R^2 was higher than 0.68 for all the varieties studied. The results obtained were grapevine variety dependent, this could be expected since varietal differences in grape hue, colour, size, and cluster compactness existed and because these differences were accentuated by the diversity in the level of ripeness among varieties at the time of image acquisition. As the variety is usually known before the image analysis this can be used to improve the results. High R^2 values (larger than 0.90) achieved for cluster weight were obtained for Bobal, Monastrell and Tempranillo, whereas more moderate prediction values were attained for Grenache and Cabernet Sauvignon (between 0.75-0.85) and for Merlot and Carignan (around 0.65) (Table 1).

Table 1. *Predicted mean R^2 value for estimation berry number per cluster and predicted mean R^2 value for the estimation of cluster weight. (n=10; p<0.001)*

Tableau 1. Valeur moyenne du R^2 pour l'estimation du nombre de baies par grappe et l'estimation du poids de la grappe. (n=10; p<0.001)

Variety	**Berry Number per Cluster Prediction, R^2**	**Cluster Weight Prediction, R^2**
Bobal	0.95	0.91
Cabernet Sauvignon	0.76	0.75
Carignan	0.95	0.65
Grenache	0.79	0.85
Merlot	0.69	0.69
Monastrell	0.94	0.91
Tempranillo	0.91	0.97

c) Analysis of the yield and leaf area under field conditions

Manual validation of the classification algorithm was conducted, showing a 98% of correct classification for the grape class and a 92% for the leaves. Most of the misclassifications in the leaves' groups were due to younger shoots and laterals, which exhibited almost the same green colour as leaves.

The correlations between the data obtained from the image analysis and the measurements of leaf area (green leaves) and yield (clusters) are shown in Figure 2. Our results showed that leaf area (R^2=0.81, p<0.001) and yield (R^2=0.73, p=0.002) per vine, can be assessed by machine vision under field conditions.

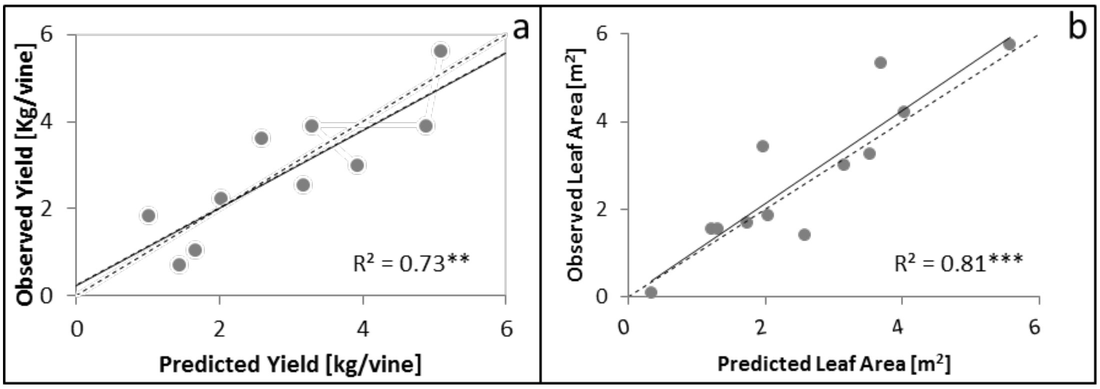

Figure 2. *Linear relationship and coefficients of correlations for (a) yield estimation and (b) total leaf area estimation using machine vision. Statistical significance:** at p<0.01; ***at p<0.001.*

Figure 2. Relation linéaire et coefficient de corrélation pour **(a)** l'estimation du rendement et **(b)** l'estimation de la surface foliaire totale avec vision par ordinateur. Signification statistique: ** pour p<0.01; *** pour p<0.001.

4. Conclusion

Results obtained confirm the proposed computer vision techniques can be applied for plant phenotyping in viticulture, to automate the assessment of some key grapevine variables, such as number of flower per inflorescence, cluster morphology, yield and leaf area. Three different scenarios have been evaluated: At inflorescence level, enabling an early estimation of yield; at cluster level, providing cluster morphology, and at canopy level assessing yield and leaf area per vine, as an important support for viticultural practices and decision-making regarding canopy management. In conclusion, machine vision offers a wide variety of applications for phenotyping in viticulture, as a fast, robust and inexpensive methodology to successfully assess key viticultural parameters.

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