Applications of Computer Vision Techniques in Viticulture to Assess Canopy Features, Cluster Morphology and Berry Size

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Abstract

Computer vision systems are powerful tools to automate inspection tasks in agriculture. Typical target applications of such systems include grading, quality estimation, yield prediction and monitoring, among others. The capabilities of an artificial vision system go beyond the limited human capacity to evaluate long-term processes objectively and provide valuable data to take decisions that will have great influence in later operations. This work explores the application of machine vision techniques in viticulture from several approaches. The first approach is aimed at working outdoors, developing in-field systems capable of assessing the canopy features of the vineyard (*Vitis vinifera* L.) by taking digital images and applying computer vision systems. The second approach is aimed at analysing cluster morphology using image analysis. Berry number per cluster and cluster weight were estimated using several algorithms of image processing. Lately, machine vision has been used as a tool to automate the measurement of berry size and weight under laboratory conditions. Manual measurement of the canopy features and yield components are tedious and subjective tasks that can be time-consuming and labour demanding. In this regard, by means of computer vision techniques, a large set of samples can be automatically measured, saving time and providing more objective and precise information.

INTRODUCTION

Machine vision systems are being used to automate inspection tasks in agriculture and food processing (Cubero et al., 2011; Lorente et al., 2012). Among other characteristics like defect detection or colour estimation, shape and size analysis are features for which image analysis provides an objective and reliable tool. This technology allows automating tasks that can be used in viticulture for different purposes.

Canopy features of the fruiting zone are related to fruit microclimate, fruit health status and grape composition (Smart and Robinson, 1991). Image analysis was applied in viticulture for assessing yield (Dunn and Martin, 2004) and the impact of early defoliation (Tardaguila et al., 2010, 2011). Machine vision has many potential applications in viticulture, as a rapid and practical method to estimate canopy features in the field.

In viticulture, cluster morphology and berry size are two key parameters, which not only impact the cluster architecture and compactness (leading to looser or tighter clusters), but are also considered as indicators of grape and wine quality (Roby et al., 2004; Matthews and Nuzzo, 2007). However, traditional methods are destructive, labour-demanding, time-consuming and of low accuracy. Computer vision could be also used for assessing cluster morphology and berry weight as a rapid and accurate method.

This work presents three approaches of machine vision in viticulture: 1) at canopy level to obtain two key parameters such as leaf area and yield, 2) at a cluster level to estimate berry number per cluster and cluster weight, and 3) to determine berry size and weight, automatically.

MATERIALS AND METHODS

Analysis of the Vineyard Canopy Features

This study was conducted in four commercial *Vitis vinifera* L. 'Tempranillo' vineyard is located in Requena (Valencia, Spain). The vineyard was trained to a vertical shoot positioning (VSP) trellis with a bilateral cordon and was pruned to retain 10 to 12 nodes. Vineyards were not irrigated during the growing season. Vines were defoliated once at the end of June (pea-size) as a common practice. Ten vines were labelled in each Tempranillo vineyard. At harvest, after image acquisition, total leaf area was assessed for each tagged vine. 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.

Image Acquisition and Processing

Assessment of canopy features was performed at harvest using digital image analysis, based on the methodology proposed by Dunn and Martin (2004) and Tardaguila et al. (2010). For each vineyard the 10 labelled vines were photographed between 09:00 AM and 11:00 AM in front of the fruiting zone of each vine 0.70 m aboveground using a digital camera (Canon EOS 550D, Japan) mounted on a tripod set normal to the canopy 2 m away from row axis and at 1.0 m above the ground. A white screen was placed behind the canopy to avoid confounding effects due to background vegetation.The digital images were cut out to include only the portion of canopy corresponding to the vine using Paint Shop Pro version 9, then analyzed using a specific image analysis algorithm developed in Matlab (Mathworks, USA). Images were divided into separated groups for training and validation processes. This program works with a selection of user defined pixels for every class in the training group of images as a starting point for a classification algorithm based on Mahalanobis distance (Tardaguila et al., 2011). 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 in the validation images (Fig. 1).

Estimation of Cluster Weight and Berry Number per Cluster

Ten clusters of *Vitis vinifera* L. 'Mourvedre' and ten clusters of *Vitis vinifera* L. 'Bobal' were collected at harvest in Requena (Valencia, Spain) and photographed in the laboratory. After image acquisition, clusters were weighed in the laboratory and berry number per cluster was manually assessed by counting the berries.

Acquisition of the Images

The images were acquired using a digital still camera (Canon EOS 550D, Japan) and the EOS Utility software provided by the manufacturer of the camera. The size of the image size was 1100 x 721 pixels and the resolution 0.38 mm/pixel. The camera was placed inside of a squared inspection chamber with directional light oriented 45º to the samples. The lighting system was composed of four lamps placed on the sides of the inspection chamber with two fluorescent tubes each (Osram Biolux L18W/965, 6500ºK) powered by high frequency electronic ballasts to avoid the flicker effect. In order to facilitate the image segmentation, the contrast between the berries and the background was increased using a uniform orange background. During the image acquisition, clusters were hanging from a clamp to not distort their shape. Four views of each cluster were acquired rotating 90º the cluster from one image to another. A total of 80 images were acquired corresponding to four images per cluster. A training set of 8 images (two clusters per cultivar) was used for tuning the algorithms and the remaining were used for tests and validation.

Image Processing Algorithms for Berry Detection

The image processing was aimed at detecting each berry in the cluster automatically. In a first step, the cluster was discriminated from the background. The segmentation method used was a threshold in the red band of the images since the contrast between the background and the objects of interest in the image was the highest.

The next step consisted on delimitating the contour of the berry. This process was done using the Canny algorithm (Canny, 1986) implemented in Matlab. This method identifies edges by looking for local maxima of the gradient in the edge, which is calculated using the first derivative of a Gaussian filter. The method uses two thresholds to detect weak and strong edges that were adjusted to 0.05 and 0.25 using the training set of images. Once the contours of the berries were extracted, the Hough transform function was used to find those contours forming circles. The input parameters required for the latter function were the radius and the minimum number of pixels that should be part of a potential circumference to be considered as such. The algorithm analysed contours representing almost 40% of a potential circle and the radius for the searched circles varied from 6 to 17 mm. The output of the algorithm yielded an array containing the coordinates of the centres and the radii of the circles detected. To avoid redundancy, within a region, all circles showing circle like contour equivalent to one third of the average radius were removed, and only the one with greater diameter, which was considered a true berry, was kept, because this was less affected by noise than fewer circles.

Tests Performed

In order to determine the accuracy of the system for predicting the total number of berries in a cluster, all clusters were manually destemmed and all the berries counted and weighted. 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 next step was to use the regression models to predict the size and weight values of the validation set.

The algorithms were tuned using the training sets of the two cultivars to know whether it was possible to obtain a unique model capable of predicting the number of berries in a cluster of any of these cultivars. To do that, a range of valid radius suitable for any size of berry of the two studied cultivars was fixed, and a minimum tolerance of the perimeter of the circumference was set.

Estimation of Berry Size and Weight

Some apparatus already exists in the market capable of estimate the volume of the berries but they are expensive and devoted for other purposes like to analyse chemical composition (Etchebarne et al., 2010; Bahar et al., 2011). Moreover, the pedicel needs to be removed since size and weight estimations and based on volume which could be influenced by the presence of the pedicel. This work describes a relatively cheap (based on a standard digital camera) method to estimate weight and size without removing the pedicel of the berries.

Plant Material

Fifty berries of *Vitis vinifera* L. 'Grenache' and 50 berries of *Vitis vinifera* L. 'Tempranillo' were used. The berries were placed on a white background and imaged using a still camera (Canon EOS 550D, Japan) to obtain images with a size of 2592 x 1944 pixels and a resolution of 0.11 mm/pixel. The berries in the images included the pedicel, therefore being necessary to detect the insertion point between the berry and the pedicel to obtain accurate measurements of both. A sample of some berries can be observed in Figure 2.

Size Estimation

The images were analysed using an image processing application developed at IVIA for this purpose. The segmentation process was done by thresholding in the blue channel because all the berries exhibited lower values of blue in the RGB (red, green, blue) colour model provided by the images, therefore showed increased contrast against the background configured in white. In the next step, an algorithm extracted the eight-connected contour by means of a chain code. The steps of the features extraction algorithm for each berry started by calculating the centroid of the objects using boundary information. Then the radius signature (Kunttu and Lepisto, 2007) was calculated. This is represented in Figure 3, where Figure 3a contains a sample of a berry with its original centroid position (4), the Figure 3b contains the radius signature (in red colour) that represents the distance of all contour points to the berry centroid. The maximum value in the radius signature (1) was located in order to find the maximum point of the contour which represents the end of the pedicel, and the two local minima were found around the end of the pedicel, (2) and (3).The next step consisted on finding the point of the contour that accomplished the line equation that passed through the base of the pedicel (calculated as the midpoint between the points, (2) and (3), and the centroid of the berry. The length of this axis is the polar diameter. A new centroid (5) is later calculated for the berry without the pedicel. Then, the equatorial diameter was finally estimated as the line oriented 90º on the polar axis that crossed the new centroid. The two points of the contour that accomplished the equation were the ends of the equatorial axis, being this considered the size of the berry.

To get the references, the same berries were individually weighed, and berry diameter and the length of each pedicel were manually measured by three independent technicians using a digital calliper in the axe stem-end-calyx and in the equatorial diameter. In order to assess the goodness of the imaging system developed predicting the size (diameter) and weigh of the berries, regression models were built on a training set of 66 out of the 100 berries. The remaining 34 berries were used for validation.

RESULTS AND DISCUSSION

Analysis of Vineyard Canopy Features

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 4. Strong relationships were observed between the yield and total leaf area and the estimated values using computer vision. Digital image analysis was also used for yield prediction in Australia (Dunn and Martin, 2004). Machine vision was used to assess defoliation impact on the canopy fruiting zone in different cultivars trained on VSP in Spain (Tardaguila et al., 2010, 2011). Our results confirm that canopy features can be assessed by a simple and computationally inexpensive method based on digital images analysis.

Estimation of Cluster Weight and Berry Number per Cluster

To obtain de total berries in the cluster, two data were used; the average number of berries per view and the total count of berries in the four images, having better results with the first approach. Figure 5 shows the results for the linear models obtained for the total number of berries and cluster weight. Figure 5a shows a strong correlation (R^2=0.962, p-value<0.05) obtained between the actual number of berries per cluster and the estimated value using computer vision. Also a good correlation has been found between the actual cluster weight and the estimated cluster weight obtained using the computer vision system (R^2=0.882, p-value<0.05).

Estimation of Berry Size and Weight

The adjusted R^2 value obtained for size estimation was 0.978 for ‘Grenache’ and 0.968 for ‘Tempranillo’. Regarding the berry weight estimation, the R^2 values achieved were 0.969 for ‘Grenache’ and 0.976 for ‘Tempranillo’, all values with a p-value<0.05

which proved the reliability of the algorithms developed. In order to properly validate the models, the next step was to use the regression models to predict the size values of the validation set. Figure 6 presents the validation results for both cultivars. The validated R^2 values were also very high, confirming the strength of the prediction model. These results indicated that the vision system developed for estimate berry size with pedicel was very reliable and could be used as a useful laboratory tool replacing current and very slow and tedious manual methods.

These results suggest that the algorithm developed was capable of correctly estimate berry size and weight, even if the pedicel was not previously removed, which can speed up some tedious and repetitive analysis tasks normally performed in laboratories. The accurate and robust method for detecting the pedicel could be also used to detect the stem of other fruits like apples, oranges or cherries with only few subtle changes in the algorithm.

CONCLUSIONS

Results obtained proved that machine vision can be a powerful technique to be used to automate different inspection tasks in viticulture and perform them accurately. Yield components estimation by image analysis could avoid the repetitive and tedious task of manual measurement of wine grape berries, since strong correlations between manual and image-derived automatic methods were obtained. The accuracy of image processing techniques in estimating the berry weight and cluster morphology provided strong linear correlations in the two studied cultivars. Finally, some canopy features of the vineyard have been successfully assessed using machine vision. This technology has many potential applications in viticulture, including yield forecast, vineyard status and cultural practices assessment.

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Figures

Fig. 1. Original (left) and segmented image (right) of a Tempranillo grapevine canopy in four different classes: clusters, green leaves, yellow-wilted leaves and porosity.

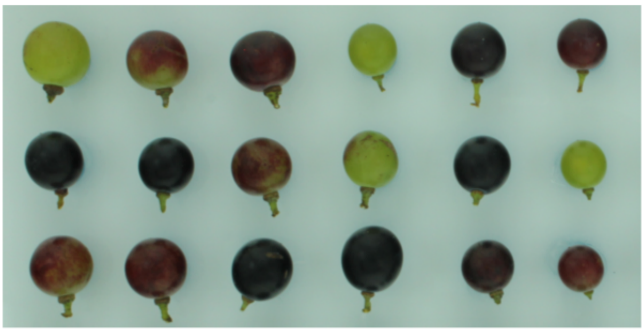

Fig. 2. Colour image with some berry samples with pedicel of *Vitis vinifera* L. 'Grenache' cultivar.

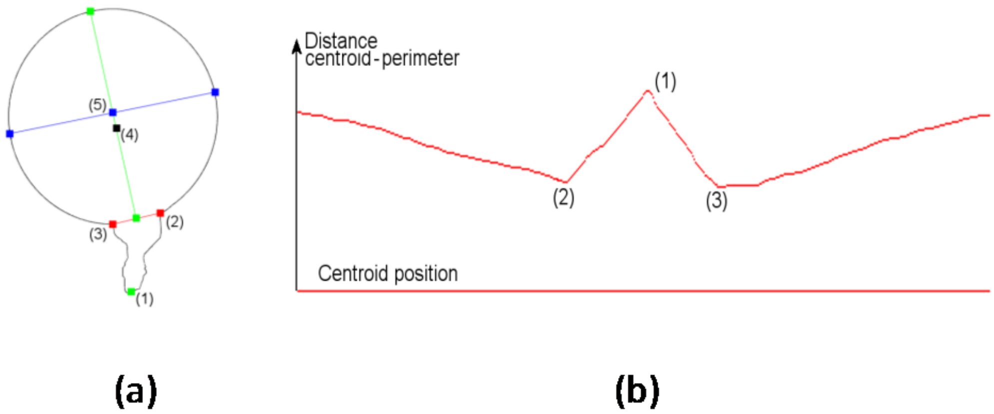

Fig. 3. a) Contour sample of a grape berry with pedicel, and b) its corresponding radius signature.

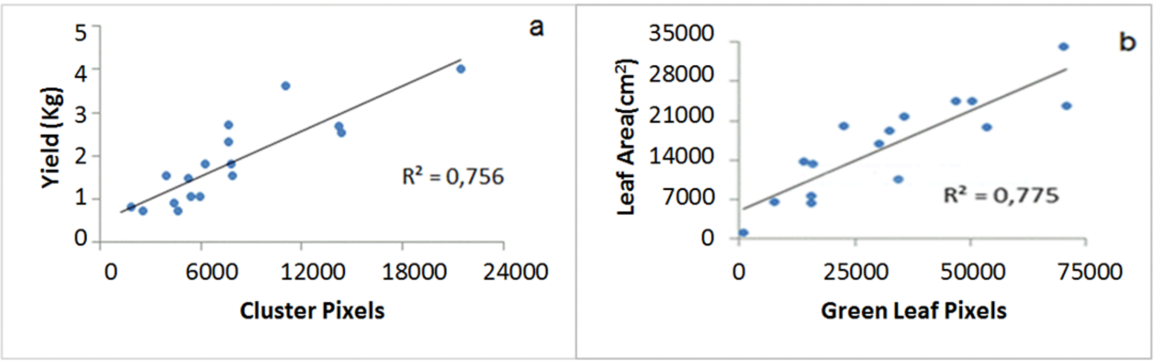

Fig. 4. Linear correlations for a) yield estimation (number of pixels in X axis and yield per vine/kg in Y axis), and b) total leaf area prediction (number of pixels in X axis and leaf area expressed in cm^2 in Y axis).

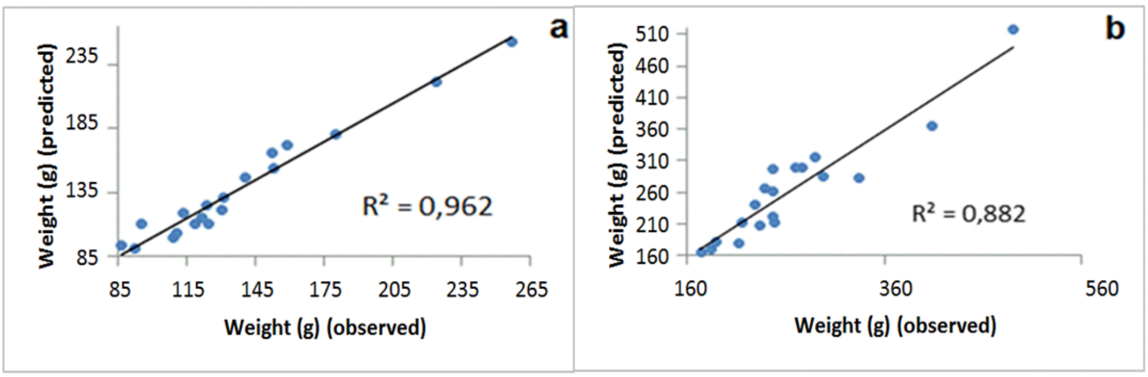

Fig. 5. Linear models for predicting a) the berry number per cluster, and b) cluster weight (g). In both cases the graphs shows predicted (Y axis) vs. observed (X axis) for clusters of 'Bobal' and 'Mourvedre'.

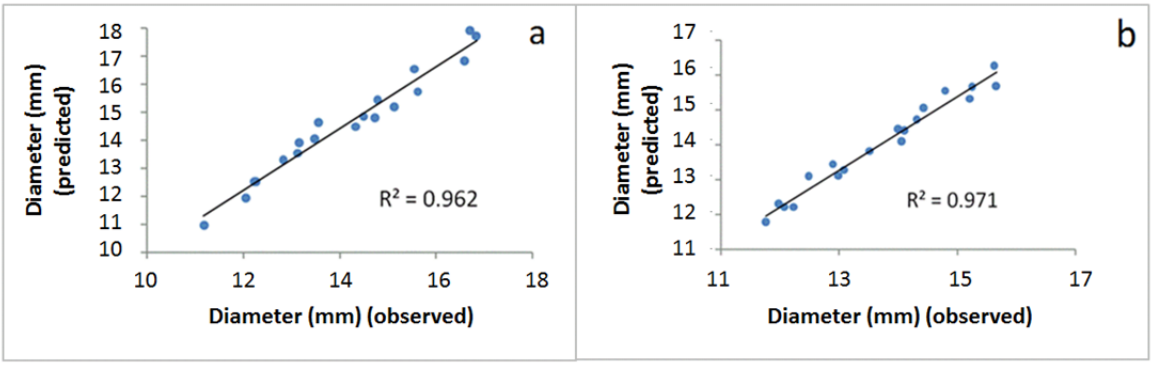

Fig. 6. Adjustment to the linear model (predicted vs. observed) for the diameter (in mm) of the berries from a) 'Tempranillo', and b) 'Grenache'.