Innovative assessment of cluster compactness in wine grapes from automated on-the-go proximal sensing application

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Abstract
Grape cluster compactness affects berry ripening homogeneity, fungal disease incidence, grape composition and wine quality. Therefore, assessing cluster compactness is crucial for sorting wine grapes for the wine industry. Nowadays, cluster compactness assessing methodology is based either on visual inspection performed by trained evaluators (OIV method) or on morphological features of clusters. The goal of this work was to develop an innovative and automated, non-destructive method to assess cluster compactness, based on computer vision on-the-go, under field conditions. RGB images were acquired on October 2016, before harvest, in a Tempranillo (*Vitis vinifera* L.) commercial vineyard. An all-terrain vehicle (ATV) was modified with equipment to autonomously capture images of 95 clusters, one week prior to harvest. Tempranillo vineyard located in La Rioja (Spain) was trained to a vertically shoot-positioned (VSP) trellis system and partially defoliated before veraison. Image acquisition was conducted using artificial illumination at night-time while the ATV moved at 5 km/h. The next day, all photographed clusters were collected, and their compactness rating was assigned by a panel of ten trained experts following the OIV 204 standard code. A combination of different machine learning and computer vision techniques was used to determine the compactness from the acquired images, obtaining a R^2 of 0.71 and RMSE of 1.208 calculated by the leave-one-out cross-validation (LOOCV), using the mean of the expert's evaluation as the reference value. These results show a strong correlation between the algorithm estimation and the average rating of a group of trained evaluators, suggesting that an automatic system can be applied to estimate cluster compactness in vineyards as an efficient alternative to traditional visual methods.

Keywords:
Computer vision, cluster morphology, RGB, machine learning, non-invasive sensing technologies, precision viticulture.

Introduction

The aggregation of the berries in the grapevine cluster defines its compactness. Cluster's compactness varies from loose clusters, which have most of the pedicels visible and a great mobility of the berries, to dense ones, with very tight berries that could even be deformed. This compactness affects to different parameters like berry ripening homogeneity, fungal disease incidence, grape composition and wine quality. Due to the subjective nature of the classic methods for assessing compactness, it is necessary to develop more objective alternatives based on new technologies, like computer vision. Computer vision aims to analyze, process and extract data from images to provide relevant information about objects and elements presented on the image. In a previous work, Cubero et al. (2015) developed a method for assessing compactness under laboratory conditions using image analysis.

The variability presented in compactness rating of clusters belonging to a given vineyard makes it necessary to obtain a high number of measurements to achieve the representativeness of the vineyard's variability. On-the-go systems can facilitate the task by reducing time required in vineyard sampling. The goal of this work is to provide an automated estimation of cluster's compactness from images acquired on-the-go in a commercial vineyard.

Materials and Methods

Images were acquired under field conditions in a commercial Tempranillo (*Vitis vinifera* L.) vineyard located in Logroño, La Rioja (Spain) in September 2016. For assessing compactness, 95 clusters were selected and numbered in the vertical shoot positioned (VSP) vineyard with the canopy partially defoliated. An all-terrain-vehicle (ATV), driven by a human operator at 5 km/h, was modified to incorporate a Sony α7II RGB camera and an artificial illumination system composed by a white LED panel for image acquisition at night time.

Fig 1. (a) On-the-go image acquisition with the modified ATV; (b) Image acquired using the artificial illumination system

After image acquisition, clusters were collected and their compactness rating was assigned by a panel of ten experts, following the proposed visual description, using the standard 204 by OIV (2009). In this method, trained evaluators perform a visual evaluation of the clusters compactness, assigning them to one of five discrete classes, which range from 1 to 9, being 1 the lowest compactness and 9 the highest one. The average of the experts rating was used as the reference value.

Image processing and analysis involves several steps (Fig. 2). Due to the unknown number of clusters in the image, an initial step of cluster detection was required, which consisted in a color-based segmentation and an extraction of histogram of oriented gradients (HOG) (Dalal and Triggs 2005) features of the bounding boxes that surround every possible candidate to cluster.

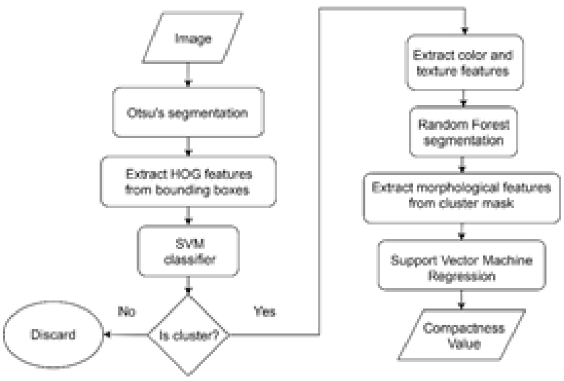

Fig 2. Flowchart of the detection and compactness evaluation using computer vision and machine learning

A Support Vector Machine classifier determined which candidates correspond to clusters. Then, color and texture information were computed for every bounding box corresponding to a cluster, so a Random Forest (Breiman 2001) classifier can extract the pixels of the berries and the rachis. The last step involves an extraction of morphological features from the mask corresponding to the cluster and its compactness is evaluated by a Support Vector Machine regression (Vapnik 1995) algorithm.

Results and Discussion

A strong correlation between cluster compactness predicted by new machine vision method and the OIV visual reference method was found (Fig 3a), obtaining a coefficient of determination (R^2) of 0.71 and a root mean square error (RMSE) of 1.208. The cluster compactness results obtained from computer vision were validated using leave-one-out cross validation (data not shown). Most of the error on the algorithm's results was caused by the difficulty of the rachis segmentation (Fig 3b and 3c), which proved to be a relevant part of the clusters mask for estimating compactness.

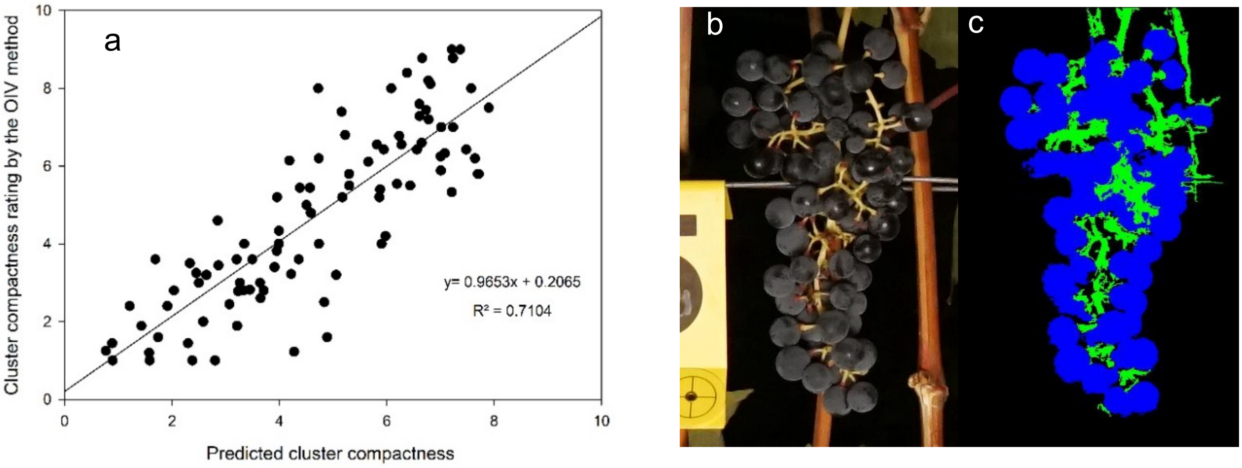

Fig 3. (a) Correlation between experts rating and the algorithm estimation (b) Cluster image; (c) Cluster segmentation: Cluster pixels identified as berries and rachis affecting cluster compactness estimation

Our results obtained from on-the-go image acquisition and under field conditions are slightly lower than the ones obtained by Cubero et al. (2015) taking four images per cluster under laboratory conditions. The new, non-invasive method can be applied for assessing cluster compactness on-the-go in commercial vineyards, using a RGB camera mounted on ATV. It leaves an open gateway for evaluating compactness spatial variability in a vineyard by taking an elevated number of samples, that could provide useful information on berry ripening homogeneity within a cluster, as well as susceptibility to botrytis fungal infection. Since this algorithm was developed for a red grape variety, modification of the segmentation methodology would be necessary to obtain a more general algorithm that could estimate compactness in white grapevine varieties as well.

In conclusion, our results show a new non-invasive proximal application, based on computer vision and machine learning, for assessing cluster compactness in red grapevine varieties, on-the-go under field conditions.

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