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Research Paper

A new methodology for estimating the grapevine-berry number per cluster using image analysis

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A new image analysis algorithm based on mathematical morphology and pixel classification for grapevine berry counting is presented in this paper. First, a set of berry candidates represented by connected components was extracted. Then, six descriptors were calculated using key features of these components, and were employed for false positive (FP) discrimination using a supervised approach. More specifically, the set of descriptors modelled the grapes' distinctive shape, light reflection pattern and colour. Two classifiers were tested, a three-layer neural network and an optimised support vector machine. A dataset of 152 images was acquired with a low-cost smart phone camera. Images came from seven grapevine varieties, 18 per variety, at the two phenological stages in the Baggiolini scale between berry set (named stage K; 94 images) and cluster-closure (named stage L; 32 images). 126 of these images were kept for external validation and the remaining 26 were used for training (12 at stage L and 14 at K). From these training images, 5438 true/false positive samples were generated and labelled in terms of the six descriptors. The neural network performed better than the support vector machine, yielding consistent Recall and Precision average values of 0.9572 and 0.8705, respectively.

The presented algorithm, implemented as a smartphone application, can constitute a useful diagnosis tool for the in-the-field and non-destructive yield prediction and berry set assessing for the grape and wine industry.

1. Introduction

Plant phenotyping evaluates the effects on the phenotype as a result of the different interactions between the diverse genotypes and the environmental conditions to which the plant has been exposed (Minervini, Scharr, & Tsaftaris, 2015; Walter, Liebisch, & Hund, 2015). A great effort is being conducted over the recent years to develop computer vision-based solutions to non-invasively capture phenotyping knowledge of the plant throughout its life cycle (Gongal, Amatya, Markee, Zhang, & Lewis, 2015; Li, Zhang, & Huang, 2014; Payne & Walsh, 2014; Spalding & Miller, 2013). In viticulture, the scientific community is pursuing the implementation of systems for vineyards optimization and management (a review can be found in Walley and Shanmuganathan, 2013).

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Nomenclature

$Berry_{cand}$	Set of found berry candidates
CIELAB, RGB	Refers to the CIE 1976 $L^*a^*b^*$ and Red-Green-Blue colour space, respectively
CCD	Charge-coupled device
CC_i, p^i	i-th connected component and set of pixel values belonging to the component
E_i, $R^1_{E_i}$, $R^2_{E_i}$	Fitting ellipse with the same normalized second central moment of a given object, and radii of the ellipse
$f_1, f_2, f_3, f_4, f_5, f_6$	Shape, normality and colour descriptors ($f_3 \ldots f_6$)
g	2-dimensional Gaussian function in the domain of integers
FN, FP, TP, PC, RC	False negative, False Positive, True Positive, Precision, Recall
h	Parameter of the h-maxima transform
I_b	Grey-level image of the b^* channel
I_{filt}	Image resulting from filtering regional maxima
I_L, I_a	Grey-level images of the L^* and a^* channel, respectively
I_{max}	Image containing relevant regional maxima
I_{maxBin}	Binary image of relevant regional maxima
K, L	Berry set and cluster closure phenological stages
L^*, a^*, b^*	L^* is the luminosity layer of the CIELAB colour space, and a^* and b^* are the chromaticity layers
min, max, $median$, #	Minimum, maximum, median and cardinal operator, respectively
p	Probability used for statistical hypothesis testing
R^2	Coefficient of determination
$R_I(j)$	Morphological reconstruction of image I from marker j
ROI	Region of interest
ROI', ROI_{def}	Images of the first and definitive computed ROI version, respectively
$\widehat{S}_i^{x^\circ}$, $d^{x^\circ}_{S_i}$	Error of symmetry in the subimage S_i across the axis at x°, sum of the elements in the axis at x°
S_i, S_i^{Gauss}	Subimage of the L^* channel; subimage containing a Gaussian distribution with a standard deviation estimated from S_i
SVM, NN, kNN	Support Vector Machine, Neural Network, k-nearest neighbour
T_{otsu}	Otsu's threshold
TPR, FPR	True and false positive rate, respectively

Some successful image-analysis models have been developed to estimate the number of flowers per inflorescence in the vineyard (Aquino, Millan, Gutiérrez, & Tardáguila, 2015; Diago, Sanz-Garcia, Millan, Blasco, & Tardaguila, 2014; Millan, Aquino, Diago, & Tardaguila, 2016). Diago et al. (2015) presented a methodology for assessing the cluster yield components based on the application of a circular model for berry boundary extraction. The analysed images were taken in the laboratory under controlled illumination conditions. Also working under a controlled environment, Liu, Whitty, and Cossel (2015) developed an algorithm for grape berry counting based on the estimation of the 3D structure of a grape cluster from a single image. Additionally, Cubero et al. (2015) proposed an algorithm to evaluate the cluster compactness, which is considered a key indicator of fruit healthiness affecting wine quality, using images taken in the laboratory. Moreover, Kicherer, Roscher, Herzog, Förstner, and Töpfer (2015) developed a computer application using Matlab including functionality for evaluating cluster length, width, compactness and berry size by means of image analysis. The application allowed evaluating cluster images acquired in laboratory. However, results obtained under restraint scenarios are hardly replicable under field conditions. Indeed, plants experience more heterogeneous situations in the field, including environmental and illumination changes or competition from adjacent plants. Moreover, the rate at which plant phenotyping information is gathered under laboratory or field conditions does not match the speed of genotyping and, as a result, a bottleneck is being produced (Houle, Govindaraju, & Omholt, 2010). Therefore, there is a need to develop accurate, robust, and automated analysis algorithms that can extract phenotypic information, preferably under "real" conditions, in the field, where plants do not grow isolated, but configuring a canopy, on crops with agricultural importance, such as grapevine (Araus & Cairns, 2014). Herzog et al. (2014), and more recently Klodt, Herzog, Töpfer, and Cremers (2015), have studied the potential of image analysis for high-throughput phenotyping in vineyards.

Diago et al. (2012) presented a methodology based on image analysis to characterise important features of the canopy, such as the percentage of exposed leaf area and clusters; the images were taken under field conditions using a reflex camera mounted on a tripod. Using this approach, another study in which the percentage of gaps and canopy porosity were evaluated was presented later on (Diago, Krasnow, Bubola, Millan, & Tardaguila, 2016). The estimation of fruit growth stage and quality has also been addressed by means of image analysis solutions. Concretely, Rabatel and Guizard (2007) developed a methodology based on approximating berry boundaries using an elliptical model to estimate berry size using in-field acquired cluster images.

However, the topic that seems to have received more attention from the scientific community is yield estimation; this is due to its relevance in vineyard management (Dusntone, 2002). Grape yield is defined by the yield components, involving the number of clusters, the number of berries per cluster and the berry size (Tardáguila, Blanco, Poni, & Diago, 2012). The number of berries per cluster is quite a very labile variable, more than other yield components, even within a given genotype (Anderson, Smith, Williams, & Wolpert, 2008; Diago et al., 2015). Indeed, it is influenced by the number of flowers per inflorescence (fertility indicator) and the fruit-set rate (percentage of flowers that become berries), both parameters being highly dependent upon the weather conditions during inflorescence development (at bud dormancy) and berry set, respectively (May, 2004). The number of berries per cluster is fully established at berry set and remains mostly invariable until harvest, determining not only the final yield but also the cluster compactness or cluster