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vitisBerry: An Android-smartphone application to early evaluate the number of grapevine berries by means of image analysis

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ABSTRACT

In agriculture, crop monitoring and plant phenotyping are mainly manually measured. However, this practice gathers phenotyping information at a lower rate than genotyping evolves, thus producing bottleneck. This paper presents vitisBerry, a smartphone application for assessing in the vineyard, using computer vision, the berry number in clusters at phenological stages between berry-set and cluster-closure. The implemented image analysis algorithm is an evolution of a previous development, providing 1.63% and 7.57% of Recall and Precision improvement, respectively. The application was evaluated using two devices, taking and analysing 144 images from 12 different grapevine varieties. The Recall and Precision results ranged between 0.8762 and 0.9082 and 0.9392–0.9508, depending on the device. The average computational time required to analyse the 144 images varied from 3.14 to 8.40 s. According to these results, vitisBerry constitutes a tool for viticulturists to acquire phenotyping information from their vineyards in an easy and practical way.

1. Introduction

Plant phenotyping quantitatively evaluates the effects of genotype interactions and the plant's environmental conditions on the phenotype (Minervini et al., 2015). The potential of image analysis for high-throughput phenotyping in vineyards is well studied (Herzog et al., 2014; Klodt et al., 2015), and multiple image-based solutions are being developed over the recent years (Rabatel and Guizard, 2007; Diago et al., 2012, 2016; Spalding and Miller, 2013; Li et al., 2014; Cubero et al., 2015; Aquino et al., 2015b).

Within plant phenotyping in viticulture by using image analysis, accurate yield assessment is of key importance, and has been identified as one of the most profitable and strategical fields of research in viticulture (Dunstone, 2002). Berry yield is defined by the yield components, involving the number of clusters, the berry number per cluster and the berry size. The number of berries per cluster is fully established at berry-set and remains invariable until harvest. It determines not only the final yield, but also the cluster compactness or cluster architecture and degree of berry aggregation (Cubero et al., 2015), which impacts berry ripening and disease incidence among other features.

There is considerable bibliography on yield prediction, with methods working either under laboratory or field conditions. On the one hand, image-based studies for berry number estimation per cluster under laboratory conditions (Diago et al., 2015; Liu et al., 2015) offer a limited applicability, as plants experience more heterogeneous situations in the field, including environmental and lightning changes and 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 et al., 2010). Consequently, image analysis algorithms towards yield prediction working under 'real' uncontrolled conditions have been presented over the recent years (Berenstein et al., 2010; Nuske et al., 2011a, 2011b, 2012, 2014; Reis et al., 2011, 2012; Fernández et al., 2013; Liu et al., 2013; Font et al., 2015). However, these methods are hardly directly applicable by viticulturists, since they often use complex mobile sensing platforms or specialized capturing devices. An analysis and a description of these methods can be consulted in Aquino et al. (2016).

Currently, there is a very mature and stablished market of mobile devices or smartphones offering a wide range of options. At this time, even low-range devices with affordable prices offer outstanding computational processing and photographic capabilities, which have made possible the development of specialized applications in multiple fields. Nevertheless, viticulture is not prolific in this sense yet, since there are only a few examples of available applications for managing vineyard features. The applications by De Bei et al. (2015) and Fuentes et al. (2012) for measuring grapevine canopy architecture, and that by Aquino et al. (2015a) and Millan et al. (2016) (vitisFlower) for assessing the number of flowers per inflorescence are surely the most remarkable among those presented.

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This paper presents the development and testing of a novel smartphone application, called vitisBerry, for counting the berry number per cluster visible in images of clusters at a phenological stage between berry-set and cluster-closure; the number of berries in a cluster image is strongly correlated to the actual number in the real cluster (Aquino et al., 2016). The application integrates the capturing and image analysis processes by exploiting the smartphone capabilities, providing the viticulturist with an easy-to-use tool to acquire phenotypic information directly in the field.

2. Materials and methods

2.1. Image analysis algorithm for berry counting in cluster images

The vitisBerry application developed for Android devices, is a novel tool for viticulturists to assess the number of berries in grapevine clusters at a phenological stage between berry-set and cluster-closure (stages K and L according to the scale proposed by Baggiolini (1952)). The application allows to take a cluster picture and implements an improved version of the algorithm presented by Aquino et al. (2016) for its analysis. As a result, the number of visible berries in the cluster is given.

The image analysis algorithm included in vitisBerry is based on mathematical morphology and pixel classification by means of supervised learning. As a pre-requisite, the photo to be analysed must be taken by placing a dark background behind the cluster. Concretely, a simple capturing box as the one shown in Fig. 1 made with a Din A3 cardboard was employed. The use of this artefact offered applicative advantages. On the one hand, it eased the individual capture of clusters, since very often they were located so close together within the grapevine, or even touching themselves, that it was impossible to photograph them individually without picking or damaging them. In addition, it also favoured the accurate extraction of a region of interest (ROI) by image analysis. Moreover, the capturing box also improved the experience with respect of using a flat cardboard, as the box's borders prevented from the generation of undesired bright spots on the berry's surface originating from light reflections on leaves or other elements.

The algorithm is divided into three main steps:

- Image pre-processing: this step is basically aimed at extracting the cluster in the image from the background. Firstly, the image is downsized to a resolution of 1170×1578 pixels (1.84 Mpx) for computational-time optimization purposes (see an example of an image acquired with the vitisBerry application in Fig. 2(a)). Then, it is converted from the native RGB to the CIE 1976 $L^*a^*b^*$ colour space (Connolly and Fliess, 1997), as this colour scheme offers the illumination and colour information decoupled, what favours the approach followed in the algorithm. Finally, the ROI is extracted by using colour discrimination criteria (see results on Fig. 2(b)); note that colour is invariant to light conditions in the CIE 1976 $L^*a^*b^*$ colour space).
- Image analysis: this step addresses the extraction of berry candidates. The detection of candidates relies on the light reflection pattern that takes place on the convex surface of berries. It is characterised by a maximum light reflection point representing the centre of a circle, progressively decreasing the reflection intensity around the centre for describing a circular pattern; this effect follows the Lambert's cosine law (Smith, 2007). Hence, berry candidates are extracted, using the extended *h*-maxima transform (Soille, 2004), by finding those connected components within the ROI being regional maxima in the lightness channel (L^*) of the CIE 1976 $L^*a^*b^*$ colour space (check Fig. 2(c)).

(a) (b)

Fig. 1. (a) Capturing box hand-made with a Din A3 black cardboard. (b) Example of image capture.