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Research Paper

A robust automated flower estimation system for grape vines

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Automated flower counting systems have recently been developed to process images of grapevine inflorescences, which assist in the critical tasks of determining potential yields early in the season and measurement of fruit-set ratios without arduous manual counting. In this paper, we introduce a robust flower estimation system comprised of an improved flower candidate detection algorithm, flower classification and finally flower estimation using calibration models. These elements of the system have been tested in eight aspects across 533 images with associated manual counts to determine the overall accuracy and how it is affected by experimental conditions.

The proposed algorithm for flower candidate detection and classification is superior to all existing methods in terms of accuracy and robustness when compared with images where visible flowers are manually identified. For flower estimation, an accuracy of 84.3% against actual manual counts was achieved both *in-vivo* and *ex-vivo* and found to be robust across the 12 datasets used for validation. A single-variable linear model trained on 13 images outperformed other estimation models and had a suitable balance between accuracy and manual counting effort. Although accurate flower counting is dependent on the stage of inflorescence development, we found that once they reach approximately EL16 this dependency decreases and the same estimation model can be used within a range of about two EL stages. A global model can be developed across multiple cultivars if they have inflorescences with a similar size and structure.

1. Introduction

Flower number per inflorescence is one of the main determinants of grapevine yield (May, 2000). The number of flowers varies between cultivars, locations and seasons, therefore accurately assessing flower number is a key opportunity to determine the potential yield early in the season (Dry, Longbottom, McLoughlin, Johnson, & Collins, 2010). The manual counting of flowers has been undertaken in both a research (Dry et al., 2010; Dunn & Martin, 2007; Petrie & Clingeleffer, 2005) and industrial context (Dunn & Martin,

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Nomenclature

AC	estimation accuracy
C	the classification result obtained by minimising inner distance of classes
e	size of element used to conduct morphological processing
F1	F1 score
I	image in RGB colour space
I_b	binary mask
I_{mask}	stem mask
k	K-means clustering algorithm
N_c	true positive value
N_{fn}	false negative value
N_{fp}	false positive value
P	a list containing FREAK feature vectors for all flower candidates
$\mathbf{p}_i$	a single element of **P**, representing FREAK feature vectors for one flower candidate
PE	percentage error
R^2	coefficient of determination
$\widehat{R}^2$	adjusted R-square value
u	coordinate of pixel in image with respect to horizontal axis
U	width of image in pixels
v	coordinate of pixel in image with respect to vertical axis
V	height of image in pixels
χ	precision
ζ	recall
$\mu_{i,d}$	mean value of a feature in class c_i

2007). In all situations the counting of flowers is an onerous proposition, and many destructive and non-destructive methods have been developed to assist this process. These include placing gauze bags over the developing inflorescences and then manually sorting and counting the flower caps (May, 2000), or photographing the inflorescence and then manually counting the flowers in the image (Poni, Casalini, Bernizzoni, Civardi, & Intrieri, 2006). While these methods allow the counting process to be completed in the laboratory, as opposed to the vineyard, they are still time consuming. Another option has been to count the number of flowers on the first branch of the inflorescence (Bennett, Jarvis, Creasy, & Trought, 2005; May, 1987) or to count the number of branches on the inflorescence (Dunn & Martin, 2007; May, 2000; Shavrukov, Dry, & Thomas, 2004) and relate this to the number of flowers on the inflorescence. These methods require calibration that is likely to vary between varieties, seasons and possibly sampling dates within a season, once again limiting their utility. An easier and more efficient and accurate method to count grape flowers would facilitate research on the impact of management practices on grapevine flowering and the use of flower counts for commercial yield estimation. This has provided the impetus for approaches based on image analysis.

Among the state-of-the-art approaches, the method proposed by (Diago, Sanz-Garcia, Millan, Blasco, & Tardaguila, 2014) based on the extended H-maxima transform has been widely applied, particularly since the method has been implemented in a free smartphone app (Aquino, Millan, Gaston, Diago, & Tardaguila, 2015). In their work, images are first segmented in the LAB colour space and then morphological operations are applied to segmented binary images and the flower number is generated after several filtering operations. At that stage, a strong relationship between detected visible flowers (flowers which are not occluded by stems or other flowers in the image) and actual flowers (total flowers in current bunch) was proven, but the actual ability of the algorithm to estimate the number of flowers per inflorescence was not characterised.

To achieve the goal of estimating the number of flowers per inflorescence by a single image, Aquino, Millan, Gutiérrez, and Tardáguila (2015) further developed visible flower detection and estimation models upon the image processing techniques. Their procedure is sensitive to colour and image size because the required threshold value and the size of structuring element varies significantly between images taken in the field. Despite this both Diago et al. (2014) and Aquino, Millan, Gutiérrez, et al. (2015) set values manually in their algorithms, and when this approach is taken for images such as that in Fig. 1 – with vigorous canopy and green grass in the background the ROI extraction fails. As for the flower segmentation, the main idea displayed by Aquino, Millan, Gutiérrez, et al. (2015) is detecting the peak reflections of flowers by Gaussian pyramidal decomposition. Following visible flower detection, three estimation models and five extracted features were investigated in regards to variety independence. Final R^2 values for the flower estimation ranged from 0.85 to 0.99.

A similar approach was presented in the work Millan, Aquino, Diago, and Tardaguila (2017), who adapted the standard procedure from Diago et al. (2014) but instead of focussing on extracting Regions Of Interest (ROIs), investigated the effects of different features on estimation models and extended the test data to 11 cultivars. The results from these improved models showed R^2 values from 0.19 to 0.99. However, the aforementioned methods are not robust or replicable because some key threshold values in their algorithms are manually set, despite the attainment of high R^2 values. Furthermore, multiple peaks existing on one flower candidate will lead to inaccuracy in flower counting. Therefore, some post-processing is required, including the elimination of false-positive detections and adding false-negative flowers.

Fig. 1 – An example of canopy in a vineyard in Australia, showing the challenging conditions faced by flower detection methods. The flagging tape visible was used for marking bunches and cordon in a separate experiment.