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Grapevine flower estimation by applying artificial vision techniques on images with uncontrolled scene and multi-model analysis

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A B S T R A C T

New technologies in precision viticulture are increasingly being used to improve grape quality. One of the main challenges being faced by the scientific community in viticulture is early yield prediction. Within this framework, flowering as well as fruit set assessment is of special interest since these two physiological processes highly influence grapevine yield. In addition, an accurate fruit set evaluation can only be performed by means of flower counting. Herein a new methodology for segmenting inflorescence grapevine flowers in digital images is presented. This approach, based on mathematical morphology and pyramidal decomposition, constitutes an outstanding advance with respect to other previous approaches since it can be applied on images with uncontrolled background. The algorithm was tested on 40 images of 4 different *Vitis vinifera* L. varieties, and resulted in high performance. Specifically, values for *Precision* and *Recall* were 83.38% and 85.01%, respectively. Additionally, this paper also proposes a comprehensive study on models for estimating actual flower number per inflorescence. Results and conclusions that are developed in the literature and treated herewith are also clarified. Furthermore, the use of non-linear models as a promising alternative to previously-proposed linear models is likewise suggested in this study.

1. Introduction

The progress of technology has produced an increased interest in the development of novel techniques in the field of viticulture. Objective and automated vineyard assessment is of special interest nowadays. In this respect, yield prediction in vineyards is probably the most challenging goal from a technical point of view, and is experimenting much interest by the scientific community (Nuske et al., 2011, 2014; Font et al., 2014; Diago et al., 2012; Roscher et al., 2014; Dunn and Martin, 2004). Yield predictions are key tools for managing vines to optimize growth and then, for improving fruit quality.

Grapevine yield is predominantly determined by two physiological processes: flowering and fruit set (May, 2004). Fruit set presents a well-known variability among varieties and clones (May, 2004; Dry et al., 2010; Galet, 1983), and can also be affected by physiological, environmental and pathological factors (Carbonneau et al., 2007). Furthermore, fruit set also shows a great inter- and intra-vine variability (May, 2004). Therefore, a count of the flower number per inflorescence is essential for its accurate estimation. Moreover, performing this task in a non-destructive manner is of vital importance for the goals of precision viticulture.

For reasons mentioned above, some methods for flower number estimation have been presented. On the one hand, May (2000) and Keller et al. (2001) proposed a method based on wrapping sample inflorescences with a fine mesh from the beginning of anthesis until fruit set completion. Then, the collected flower caps in the mesh were manually counted in order to estimate the number of flowers per cluster. This method, in spite of being valid, is time consuming and labour demanding. On the other hand, Poni et al. (2006) proposed the use of digital photography for flower number estimation. First, the authors photographed each sample inflorescence in a study set against a dark background. Then, the number of flowers present in each image was manually counted. Finally, the real number of flowers per inflorescence was estimated using a linear model. This model performed a linear regression between actual flower number and the flower number manually counted on photos. The model was calibrated using data from twenty inflorescences taken from extra vines. The work by Poni et al. (2006) represented a conceptual advance in the estimation of flowers per inflorescence, since its automation would extremely decrease the workload from previous approaches. To this extent, Diago et al. (2014) developed an automated methodology for counting flowers

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in inflorescences by means of image analysis. Images were taken placing a dark background cardboard behind inflorescences for facilitating the calculation of a region of interest (ROI). After ROI extraction using colour discrimination, flowers were detected by recognising the reflection pattern produced by the light on the surface of flowers. Finally, the authors studied correlation between the number of flowers present in an image and the real number of flowers in its corresponding inflorescence. As a result, acceptable correlations per variety were found, whereas correlation of the defined variables was poorer considering varieties as a whole. This result led authors to discuss the suitability of using individual linear models per variety instead of a general one. To the best of the authors' knowledge, despite artificial vision is increasingly being applied to viticulture, the work by Diago et al. (2014) is unique for the automated estimation of flower number per inflorescence.

The present paper proposes a new methodology for the automated segmentation of flowers in inflorescence images under field conditions by means of morphological image processing and pyramidal decomposition. The algorithm is capable of working without the need of placing a dark background cardboard behind the inflorescences. This feature eases the use of the algorithm in field, since the cardboard is uneasily placed in specific situations, and likewise gets wet or dirty, or even torn. Moreover, the process of placing the dark cardboard and taking the photo at the same time is hardly performable by a person alone. Additionally, a rigorous study on models for the estimation of real number of flowers per inflorescence from flowers counted on images is presented. Conclusions from results of this study do not completely match with those previously developed by other authors. Therefore, authors find necessary a more in depth study and discussion over the results appearing hereafter.

2. Material and methods

2.1. Image acquisition

For developing and testing the segmentation algorithm, 40 inflorescence RGB images of *Vitis vinifera* L. cvs Airen, Albariño, Tempranillo and Verdejo were acquired, 10 per variety, in a commercial vineyard located in Vergalijo (Navarra, Spain), during May 2014 season. Phenological stage of varieties was 18, according to the scale proposed by Coombe (1995) (flower caps still in place, but cap colour fading from green). RGB images were captured at 6000 × 4000 pixels in size (24 Mpx), 8 bits per channel, using a Nikon D5300 reflex camera (Nikon corp., Tokyo, Japan); no tripod was used. The lens used was a Sigma (Sigma corp., Kanagawa, Japan) 50 mm F2.8 macro. With respect to camera configuration, the settings for the main parameters were:

- Diaphragm opening: to obtain the maximum field depth provided by the lens, the minimum value (f/36) was used.
- ISO sensitivity: it was set to values providing proper image illumination.
- Shutter speed: this parameter was automatically set by the camera.

Two criteria were applied in the acquisition process to ensure appropriate image illumination:

- Capturing inflorescences facing the Sun. The opposite orientation leads to light reflection and refraction patterns that can negatively affect the results.
- Casting a shadow on the scene. Since the Sun is located behind the photographer due to the previous criterion, he/she can easily cast a shadow with his/her own body on the inflorescence to create a homogeneous illumination for the scene.

The distance between the camera lens and the inflorescence was not pre-established, but this was considered to be around 30–50 cm. No artificial lighting system or background homogenisation were used in order to mimic the variable outdoor conditions.

The 40 inflorescences photographed for creating the described set were not cut, since they were monitored until harvest. As a consequence, the total number of flowers, indispensable data for developing the estimation models study, could not be counted. This is why, with this purpose, a new set of 48 images of the same varieties (12 per variety) were taken under the same conditions than those previously detailed.

2.2. Methodology for flower segmentation in inflorescence digital images

The methodology proposed for flower segmentation was divided into two main phases: the ROI extraction (Section 2.2.2) and flower segmentation (Section 2.2.3). A flow-chart diagram illustrating the most relevant processes involved in the whole image analysis is shown in Fig. 1. As a preliminary step, images were scaled down to a resolution of 1500 × 1000 pixels in size (0.25 times the original size) for reducing computational workload. Another important decision was the selection of the image colour space used. Images were taken according to the RGB colour scheme (this is determined by the constructive features of the camera sensor); however, this scheme did not properly represent image information in this study. Conversely, the HSV colour space represents structured image information into three noteworthy axes: hue, saturation and value. The hue channel condenses information on the colour shade; the saturation expresses its pureness; and the value its lightness. Therefore, RBG images were converted to HSV colour space prior to being processed.

Much of the processing carried out in this paper is based on mathematical morphology. In the first Section 2.2.1, a brief description of this image processing technique along with mathematical definition of operators used throughout the paper is developed.

2.2.1. Mathematical background and operator's definition

Mathematical morphology is a nonlinear image processing used to extract structures of interest from the image. Comprehensive manuals about this technique can be found in Serra (1982) and Soille (2004). Nevertheless, for completeness purposes, a brief review of morphological operators used in this paper is carried out in this section.

Let f be a greyscale image. Image f is a mapping of a subset D_f of $\mathbb{Z}^2$, which is the definition domain of the image, into a bounded set of nonnegative integers N_0:

$$f: \ D_f \subset \mathbb{Z}^2 \rightarrow \{0, \ldots, t_{max}\}$$

where t_{max} is the maximum value of the data type used (e.g., 255 for 8-bit images, 1 for binary images, ...). The complementary image of f, denoted as f^c, is defined for each pixel x as the maximum value of the data type used minus the value of the image f at pixel x:

$$f^c(x) = t_{max} - f(x)$$

The intersection of two greyscale images f and g is defined as

$$f \wedge g = \min[f(x), g(x)]$$

where *min* stands for the minimum operation. Similarly, the union of two images f and g would be

$$f \vee g = \max[f(x), g(x)]$$

being *max* the maximum operation.