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A computer vision system for early stage grape yield estimation based on shoot detection

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ABSTRACT

Counting grapevine shoots early in the growing season is critical for adjusting management practices but is challenging to automate due to a range of environmental factors.

This paper proposes a completely automatic system for grapevine yield estimation, comprised of robust shoot detection and yield estimation based on shoot counts produced from videos. Experiments were conducted on four vine blocks across two cultivars and trellis systems over two seasons. A novel shoot detection framework is presented, including image processing, feature extraction, unsupervised feature selection and unsupervised learning as a final classification step. Then a procedure for converting shoot counts from videos to yield estimates is introduced.

The shoot detection framework accuracy was calculated to be 86.83% with an F1-score of 0.90 across the four experimental blocks. This was shown to be robust in a range of lighting conditions in a commercial vineyard. The absolute predicted yield estimation error of the system when applied to four blocks over two consecutive years ranged from 1.18% to 36.02% when the videos were filmed around E-L stage 9.

The developed system has an advantage over traditional PCD mapping techniques in that yield variation maps can be obtained earlier in the season, thereby allowing farmers to adjust their management practices for improved outputs. The unsupervised feature selection algorithm combined with unsupervised learning removed the requirement for any prior training or labeling, greatly enhancing the applicability of the overall framework and allows full automation of shoot mapping on a large scale in vineyards.

1. Introduction

Accurate yield estimation for wine grapes is essential for improving winery efficiency and wine marketing strategies. In addition to this, an accurate early season forecast allows growers to sensibly regulate vineyard yields to meet grape quality targets. Existing traditional yield estimation approaches can be used as early as bud burst, and generally require a bud, bunch, or berry counts (Martin and Dunn, 2003), requiring expensive and time consuming in-field measurements. These measures are often biased prone to error. An automated system has the potential to eliminate human error and reduce labor costs. In recent years, the application of image processing techniques to obtain data in vineyards and facilitate better forecasting has become a major research focus. These studies fit into two broad groups: 1. the detection of a single object of interest from a small group of images, or 2. extracting pertinent information from images on a large scale.

For the group 1, in-field detection techniques have been used to characterize disease (Meunkaewjinda et al., 2008), and vine components (Correa et al., 2011; Fernández et al., 2013; Klodt et al., 2015) from individual or stereo images. However, the techniques requires substantial processing time and images must have consistent illumination and composition. Furthermore, they require custom or stationary rigs to obtain stable imagery (Correa et al., 2011; Diago et al., 2012), which on a vineyard scale becomes a slow or expensive process. Requirements for a particular vine component to be present within an image for correct segmentation (Correa et al., 2011) requires further automation to increase feasibility, and classifications on a pixel level are also slow and not recommended for large-scale image processing. Thus, a robust in-field

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method is required. Liu and Whitty (2015) proposed an approach to detect bunches in natural environmental conditions by a Support Vector Machine. The work done by Liu et al. (2013) and Font et al. (2015) investigated relationships between grape bunch weight and single image descriptors generated by different image processing methods. Dorj et al. (2013) demonstrated a color segmentation approach to detect tangerine flowers. However, none of these studies explored relating detection results to final yield. The cost and robustness of these detection methods have not been tested for larger scale implementation.

Most recently, Payne et al. (2013), Wang et al. (2013) and Nuske et al. (2014) investigated yield forecasting through image processing. Their work is not limited to object detection but rather converts the detection results into a final yield after being combined with manual field sampling. This has provided a solution to estimate the final yield by image processing but only after the fruit

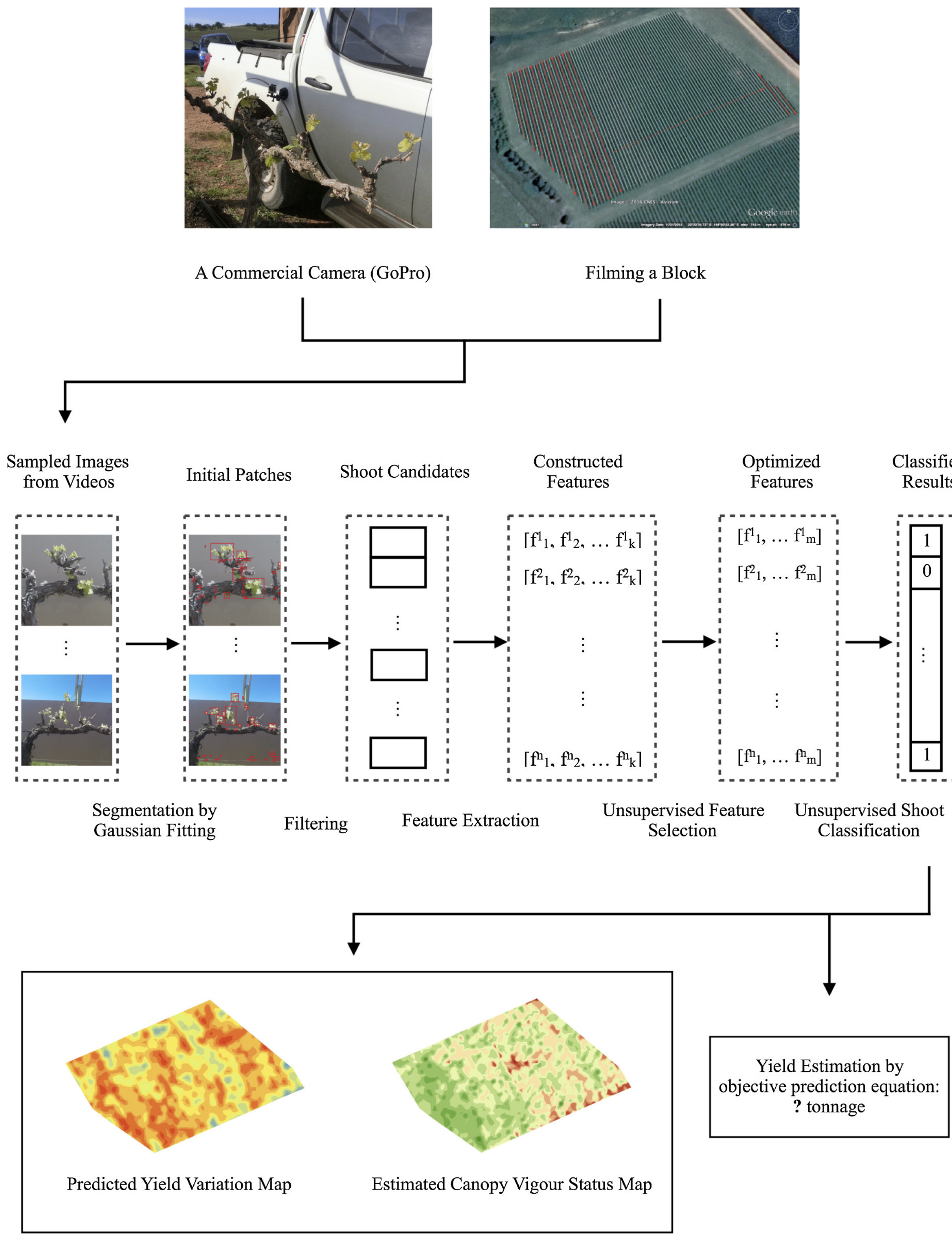

Fig. 1. Flowchart of the system for yield estimation presented in this paper based on computer vision, labeled with corresponding sections of this paper.