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Automated image analysis framework for high-throughput determination of grapevine berry sizes using conditional random fields

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ABSTRACT

The berry size is one of the most important fruit traits in grapevine breeding. Non-invasive, image-based phenotyping promises a fast and precise method for the monitoring of the grapevine berry size. In the present study an automated image analyzing framework was developed in order to estimate the size of grapevine berries from images in a high-throughput manner. The framework includes (i) the detection of circular structures which are potentially berries and (ii) the classification of these into the class 'berry' or 'non-berry' by utilizing a conditional random field. The approach used the concept of a one-class classification, since only the target class 'berry' is of interest and needs to be modeled. Moreover, the classification was carried out by using an automated active learning approach, i.e. no user interaction is required during the classification process and in addition, the process adapts automatically to changing image conditions, e.g. illumination or berry color. The framework was tested on three datasets consisting in total of 139 images. The images were taken in an experimental vineyard at different stages of grapevine growth according to the BBCH scale. The mean berry size of a plant estimated by the framework correlates with the manually measured berry size by 0.88.

1. Introduction

Grapevine (V.vinifera L. subsp. vinifera) is one of the oldest and one of the economically most important fruit crops. Grapevines are highly susceptible to various diseases like powdery and downy mildew requiring high plant protection efforts. Hence, grapevine breeders around the world select for high disease resistance, climatically well adapted and high quality new cultivars (Töpfer et al., 2011). Due to the specific cultivation of grapevines as a perennial plant e.g. fruit traits can only be evaluated in the vineyard and are highly influenced by environmental factors. Their evaluation requires several repetitions. Up to now phenotyping of grapevines in vineyards has been carried out by estimation applying the BBCH scale (Bloesch and Viret, 2008) or OIV descriptors (OIV, 2001). It is very time consuming, requires a lot of expertise and is expensive. The resulting data are subjective which make subsequent analysis more difficult like the identification of new Quantitative Trait Loci (QTL). Accurate phenotyping is the key tool for future plant breeding. Objectivity, automation and precision of phenotypic data evaluation are crucial in order to reduce the phenotyping bottleneck.

The application of digital image analysis tools and image interpretation techniques promise a technology for high-throughput phenotyping in order to (a) increase the quantity of phenotyping samples, (b) to improve the quality of recording and (c) minimize error variation. Low-level analysis tasks such as finding geometric objects (e.g. Peng et al., 2007; Chan and Shen, 2005) as well as tasks with introduced semantic higher-level information have been dealt within the literature for various applications. Especially, higher-level knowledge about the context and the spatial arrangement of objects have been early proved beneficial for object detection or semantic image segmentation (e.g. Bar and Ullman, 1996; Biederman et al., 1982; Palmer, 1975). A well established way to incorporate this knowledge is the utilization of a conditional random field, which was introduced by Lafferty et al. (2001). It has been used for example by Gould et al. (2008) and Galleguillos et al. (2008) as well as Rabinovich et al. (2007) in order to incorporate semantic context between detected objects of different predefined classes. Another approach was applied by Lafarge et al. (2010) or Descombes et al. (2009), who extract different kinds of

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geometric objects with point processes yielding an optimal object configuration. Such approaches assume that the objects are disconnected from each other and the background is distinct enough so that the objects are clearly visible (Lempitsky and Zisserman, 2010). This situation is not always given, even less for phenotyping in the field.

One challenge in digital image analysis for high-throughput phenotyping is that only one target class, such as 'berry', is of interest. Other classes, which are necessary for multi-class classification, are hard to gather and cannot be specified in many cases due to their high intra- and inter-class variety. In order to overcome this problem, the concept of one-class classification has been introduced, which distinguishes one target class from all other classes without explicitly defining them (e.g. Khan and Madden, 2010; Tax, 2001; Moya and Hostetler, 1993). In this framework, both conditional random fields and an one-class classifier are combined in order to find objects which belong to the target class 'berry'. Similar to Song et al. (2013), who are using a conditional random fields in order to model temporal dependencies in an one-class dataset, this framework exploits information of the spatial arrangement of berries in clusters. Moreover, the framework uses an active learning approach (Settles, 2010) which defines the one-class dataset from scratch in each image. This has the advantage that no human user interaction is required during classification process and in addition, the process adapts automatically to changing conditions, e.g. illumination or berry color.

Image-based detection of grapes is known from precision viticulture. For example, Nuske et al. (2011) detect and count berries for yield estimation, Berenstein et al. (2010) detect and localize berry clusters for selective spraying or Mazzetto et al. (2010) monitor canopy health and vigor utilizing optical and analog sensors. Image-based phenotyping in vineyards in order to support the identification of new molecular marker for grapevine breeding comprises more detailed detection and survey of small structures, e.g. single grapevine berries. The grapevine berry size is one of the most important target fruit traits in viticulture (Fanizza et al., 2005; Cabezas et al., 2006; Costantini et al., 2008), whereas grapevine cultivars should preferentially have uniformity size of berries (Beslic et al., 2009). In general, the berry diameter is estimated by experts applying the OIV descriptor number 221 (OIV, 2001). This descriptor enables the classification of the berry size into five classes (class 1: very narrow berries up to about 8 mm; class 2: narrow berries about 13 mm; class 3: medium berries about 18 mm; class 4: wide berries about 23 mm; and class 5: very wide berries about 28 mm and more). The results of the visual estimated berry diameter by humans are subjective resulting in error variations between the results of different people. In addition, precision from only 5 mm could be achieved, which is too inaccurate for precise berry size QTL calculations. Moreover, it should be noted that the manual estimation of sufficient amounts is very time consuming and consequently the classification of the berry size is only feasible on selected breeding material. Minor differences in berry sizes of only 1–2 mm have to be achieved on thousands of grapevines at few days (ensure comparability of records), which is possible using image-based approaches. The framework presented in the current study aimed at an automated estimation of the size of grapevine berries from single images, which were taken in an experimental vineyard at different developmental stages. Hereby, the detection of representative berries and the determination of their diameter will be included.

The field experiments, obtained plant material and images are introduced in Sections 2.1 and 2.2. In Section 2.3 the proposed framework and its parts are introduced. Section 2.4 explains the introduced parts in more detail. The experiments and the obtained results are showed and discussed in Section 3. The paper concludes in Section 4.

2. Material and methods

2.1. Plant material

Field experiments were conducted during the growing season of 2012. Tests involved rows of the Vitis vinifera ssp. vinifera cultivars 'Riesling', 'Pinot Blanc', 'Pinot Noir' and 'Dornfelder' at the experimental vineyard of Geilweilerhof located in Siebeldingen, Germany (N 49° 21.747, E 8° 04.678). Fifteen plants per cultivar were used for image acquisition and the measurement of reference data.

2.2. Image acquisition and reference measurements

Image acquisitions were carried out using a single-lens reflex (SLR) camera (Canon® EOS 60D). Camera calibration was performed according to Abraham and Hau (1997) with a wide-angle of 28 mm equivalent focal length. Images (8-bit RGB, 3456×2304 pixel) of grapevines were captured in the vineyard with a distance of about 1 m at three different plant development stages BBCH 75, BBCH 81 and BBCH 89 (Bloesch and Viret, 2008). The images were acquired under natural illumination field conditions with manually controlled exposure. Images were saved for offline processing. Reference measurements were conducted manually in parallel to image acquisition. Therefore, 50 berries per plant, cultivar and BBCH stage were randomly selected to measure the berry diameter by the utilization of an electronic calliper (Insize® Co. LTD, Conrad electronics SE, Hirschau, Germany). In order to transform measurements in the images from pixel to mm, colored labels with a width of 13 mm (Roth® GmbH, Karlsruhe, Germany) were fixed on the wires in the vineyard.

2.3. Framework

A five-step framework was developed using Matlab® (Mathworks, Ismaning, Germany) in order to extract phenotypic data from images (Fig. 1). The steps include various image analyzing tools and interpretation methods, which are explained in more detail in Section 2.4. The challenge of the framework is the detection of as many berries as possible in order to extract a representative amount of phenotypic data while keeping the error rate of falsely detected berries as low as possible in order to ensure a high quality of the extracted data.

(Step 1) Pre-processing: The image is adjusted automatically regarding brightness, color and contrast in order to compensate illumination effects. For this the image is converted into the YIQ color space and adjusted, whereas Y is the luminance and I and Q contain the chrominance information. Moreover, the contrast is stretched.

(Step 2) Detection of circular structures (*see* Section 2.4.1): Two sets of circles are determined using circular Hough transform (Peng et al., 2007):

- Automated detection of reference circles $\mathcal{R}$: Reference berries are image patches which are showing distinct circular structures. Assuming that the most dominant circles in one image are berries which can be used as training data in the classification process, the circle detector is applied with high constraints, i.e. the detector returns only very distinct circles.
- Automated detection of berry candidates $\mathcal{C}$: Candidates for grapevine berries are all image patches which consist of at least a weak circular structure potentially showing a berry. The candidates are extracted by the circle detector using weak constraints, i.e. the detector also returns circles with low responses. The reference set is a subset of the candidate set,