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Phenoliner 2.0: RGB and near-infrared (NIR) image acquisition for an efficient phenotyping in grapevine research

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Abstract In grapevine research, phenotyping needs to be done for different traits such as abiotic and biotic stress. This phenotypic data acquisition is very time-consuming and subjective due to the limitation of manual visual estimation. Sensor-based approaches showed an improvement in objectivity and throughput in the past. For example, the 'Phenoliner' a phenotyping platform, based on a modified grape harvester, is equipped with two different sensor systems to acquire images in the field. It has so far been used in grapevine research for different research questions to test and apply different sensor systems. However, the driving speed for data acquisition has been limited to 0.5 - 1 km/h due to capacity of image acquisition frequency and storage. Therefore, a faster automatic data acquisition with high objectivity and precision is desirable to increase the phenotyping efficiency. To this aim, in the present study a prism-based simultaneous multispectral camera system was installed in the tunnel of the 'Phenoliner' with an artificial broadband light source for image acquisition. It consists of a visible color channel from 400 to 670 nm, a near infrared (NIR) channel from 700 to 800 nm, and a second NIR channel from 820 to 1,000 nm. Compared to the existing camera setup, image recording could be improved to at least 10 images per second and a driving speed of up to 6 km/h. Each image is geo-referenced using a real-time-kinematic (RTK)-GPS system. The setup of the sensor system was tested on seven varieties (Riesling, Pinot Noir, Chardonnay, Dornfelder, Dapako, Pinot Gris, and Phoenix) with and without symptoms of biotic stress in the vineyards of Geilweilerhof, Germany. Image analysis aims to segment images into four categories: trunk, cane, leaf, and fruit cluster to further detect the biotic stress status in these categories. Therefore, images have been annotated accordingly and first results will be shown.

Keywords Multispectral camera, image acquisition, geo-information, *Vitis vinifera*, field phenotyping

1 Introduction

Vitis vinifera (Grapevine) is considered to be one of the most economically important fruit crops worldwide with 7.4 million ha and an annual production of 78 million tonnes in 2018. In France and Germany, 99% of the grapes are grown for wine production [1]. The yield and vine health, including wine quality are regarded as the most important economic indicators for viticulturists [2]. Grapevine is highly susceptible to several diseases, such as powdery mildew and downy mildew, of which the infection can result in a significant reduction of total soluble solids in berries and further cause a negative effect on total glucose and fructose content, total red pigments, and thus alcohol content in wine [3, 4]. Therefore, the grapevine breeding activities mainly focus on selecting new varieties with high abiotic and biotic stress resistance and high quality characteristics [5]. As a perennial woody plant, observation of phenology, analysis of growth habits (grapevine architecture), and evaluation of yield are very time-consuming and can only be conducted in the field. Most of these characteristics need to be evaluated within a narrow time window resulting in limitation of phenotyping workload and somewhat limited efficiency of grapevine breeding. Therefore, faster sensor assisted phenotyping methods with high objectivity and precision have been intensively investigated in recent years to screen breeding material, such as number and size of beeries or clusters [6,7], berry skin characteristics [8], leaf area [9], cane mass [10], diseases recognition [11–13] etc.

Due to the improvement of pattern recognition algorithms, computation capability, and image quality in recent years, computer vision is being applied in agriculture [14] for disease detection in rice, maize, coffee, grapevine etc. [15–18]. To develop a more precise and faster tool for identification of plant disease by computer vision, the convolutional neural network (CNNs) techniques are numerously used. So far, most of the published methods applied for symptom detection are based on digital images acquired using wavelength of visible and near-infrared range of the spectrum [19]. With increasing optimization of algorithms, sensor-based approaches showed an improvement in objectivity and throughput in disease sensing in the past. In grapevine research, several sensor techniques have already been tested for various applications, including pre-symptomatic and symptomatic disease sensing [13, 20, 21]. Both ground-based hyper- and multispectral imaging are proven to be suitable for detection of foliar symptoms of esca trunk disease and powdery mildew infection in vineyard achieving overall accuracies of 82-83% and 87%, respectively [13, 22]. By combining the biophysical- (e.g. content of chlorophyll, carotenoid and dry matter) and texture parameters during classification, the accuracy to predict esca disease was increased from 81% to 99% [23]. However a hyperspectral sensor, which covers a broader wavelength range to acquire more information, is usually expensive and bulky. Therefore, using multispectral or Red Green Blue (RGB)-cameras for image capture would be more feasible in agricultural applications.

Meanwhile, several platforms, such as *PHENObot* [24], Phenoliner [25], grape-picking robot [26] or unmanned aerial vehicle [27], have been developed to carry the sensor systems for sensing in vineyard or machinery picking of fruit. However, the operating speeds of these platforms is either too slow to adapt to the usual operating speed of field working machines or provides images with low resolution. Therefore, to improve the efficiency of machinery phenotyping, an update of the former screening platform 'Phenoliner' was conducted in the present study to optimize the automated image acquisition in the field, data management, and data analysis.

2 Material and methods

As described by [25], the ERO-Grapeliner SF200 (ERO Gerätebau, Simmern, Germany), of which all units for harvesting, including the hydraulic system were removed, served as a carrier for the sensor system. A generator driven by the vehicle was conducted to provide the energy to operate the sensors, light units, and computers.

2.1 Plant Materials

Field trials were conducted in September 2020 in the experimental vineyards at the Julius Kühn-Institut Geilweilerhof, Siebeldingen, Germany (49°13’06.0”N, 8°02’48.2”E). Seven varieties including red and white grapevine cultivars , i.e., Riesling, Pinot Noir, Chardonnay, Dornfelder, Dapako, Pinot Gris, Calardis Musqué and Rieslaner with and without symptoms of biotic stress were used for testing.

2.2 *SmartVision* Camera System

In the present study, the embedded image processing system *SmartVision* from Fraunhofer IOSB was used. The *SmartVision* system includes the user-interface, camera control, image acquisition and real-time image processing unit with artificial intelligence. Furthermore, *SmartVision* provides a machine-to-machine interface based on OPC-UA (Open Platform Communications Unified Architecture) using the open source implementation *open62541*. This allows the system to be controlled remotely and additional sensors can be added.

The system is equipped with a prism-based simultaneous multispectral camera system (Fusion Series FS-3200T-10GE-NNC, JAI A/S, Germany) with a 8 mm lens (VS-0818H/3CMOS, Pyramid Imaging, USA) and was installed in the right part of the tunnel of the ‘Phenoliner’ with an artificial light source for image acquisition as in figure 2.1. This camera system consists of a visible color channel from 400 to 670 nm, a near infrared (NIR) channel from 700 to 800 nm, and a second NIR channel from 820 to 1,000 nm. The camera system has 2048 x 1536 active pixels and single/multi-readout mode for each channel, which provides a high resolution and speed with lower processing loads. To minimize the direct sunlight interference, curtains were used on the opening of the tunnel, and therefore, five LED light lamps (Lumimax LB500-44-W, IIM AG, Germany) were installed to achieve efficient light conditions during image acquisition. In order to achieve a better image of NIR and further increase the driving speed, two broadband NIR LED bars

(EFFI-Flex, EFFILUX GmbH) were installed in addition at the side of the camera. The distance of the camera to the grapevine plants and the height of the captured region were illustrated in figure 6.1(e). The camera system was ported to a separated mini computer (MAGNUS EN072070S, Zotac, Hongkong, China) extended with WLAN access point, which serves as local host and was placed on the top platform of the harvester to process the image on-board. A 1 T of fast solid-state disc drives (EMTEC X200 Portable SSD, 450MB/s transfer speed) was used for storage of data.

To reference the geographic information to each grapevine, a real-time-kinematic GPS system (SPS852, Trimble, Sunnyvale, USA) was installed. The GPS antenna is located on top of the vehicle (Fig. 6.1(d)) and the receiver provides standardized National Marine Electronics Association (NMEA) strings for the camera system as described by Kicherer *et al.* (2017).

3 Image acquisition

The SmartVision system provides a WLAN access point and the user interface is accessible using an internet browser. Both signal intensity and visible images from both RGB- and NIR-channels are shown (Fig. 3.1), which gave the operators more information to evaluate the quality of image acquisition in the field. The developed program also provides an automatic evaluation of exposure of the images. To gain a better quality of the image several camera parameters, such as cycle time, integration time, and exposure balance were adjusted accordingly. In the end, a cycle time of 100 ms and an integration time of 9 ms were set to achieve a good image acquisition with 10 images per second at a driving speed of up to 6 km/h. This operating speed is much faster compared to the former Phenoliner setup, which is only able to move at a speed of 0.5 - 1 km/h when capturing the images with a frequency of 5 images per second [25]. Meanwhile, GPS information was taken and stored.

During the image acquisition, the program displayed the status of the application, i.e., number of image files, remaining disk space, camera frame rate etc. as well. The acquired images were saved in a hierarchical data format (hdf5) and further archived in folders with metadata

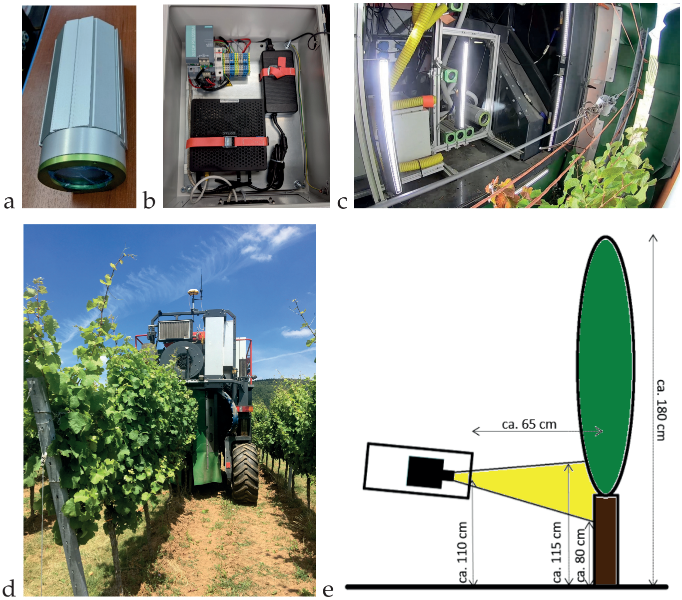

Figure 2.1: Construction of sensor system on Phenoliner. a) container for the camera, b) computer including WLAN access point for image processing, c) sensor and light units in the tunnel of Phenoliner, d) image acquisition by Phenoliner in the vineyard, e) scheme of distance.

correspondingly. The acquired images will be further processed to be segmented into four classes (trunk, cane, leaf, and fruit cluster) manually using software 'Labeltool' (Fraunhofer IOSB). Under classes of cane, leaf, and fruit cluster, at least two sub-classes, healthy and diseased (including different disease severity levels) will be given.

4 Prospective phenotyping pipeline of Phenoliner 2.0 in viticultural and grapevine breeding

As the acquisition of images with high quality and at normal working driving speed has been successfully tested in vineyards in the present study, an opportunity to apply this sensor system in two different areas

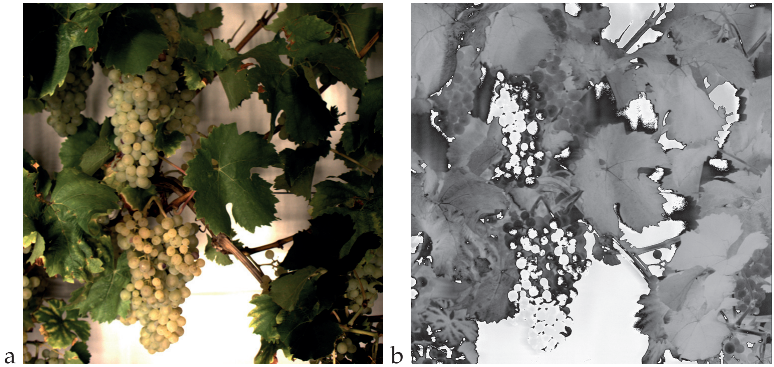

Figure 3.1: RGB Image (a) and normalized difference vegetation index (NDVI) image using RGB and NIR data (b).

is expected. On the one hand the use in grapevine breeding to describe and screen breeding material and on the other hand to improve mechanical harvest in viticulture.

Both applications have a slightly different workflow and in some steps different parameters of interest. The pipeline for both applications is shown in Figure 4.1. For mechanical harvesting a trained model based on automatic detection is planned to help the grape harvester make a yes or no decision for harvesting. This could be achieved by controlling the on and off function of the shaking units, and therefore the diseased fruit clusters could be excluded to increase the harvest quality. The application of this sensor system in grapevine breeding aims at screening selection criteria like yield and plant health fast and objective in the field. Besides the estimation of yield, the distinction of different diseases, as well as the disease incidence and severity, are relevant for the description and selection of breeding material. For digital documentation of phenotyping data, the processed results referenced to geographic information will be recorded and saved in a database. Based on the recorded data, a map with information of yield, the health status of the individual grapevine can be generated. In case of the breeding application it opens the opportunity to evaluate different breeding material over several years comparably, also retrospective if new phenotyping tools may be available.

In further experiments, this constructed sensor system could be installed in front of a commercial grape harvester and used under natural sunlight that does not provide a stable light condition compared to the Phenoliner, to investigate whether it enables the sensing of the grapevine status in real-time during harvesting. This will open up the opportunity to use such a sensor system in viticulture in the future to help the wine grower to improve his plot performance, adjust vineyard management and increase his wine quality.

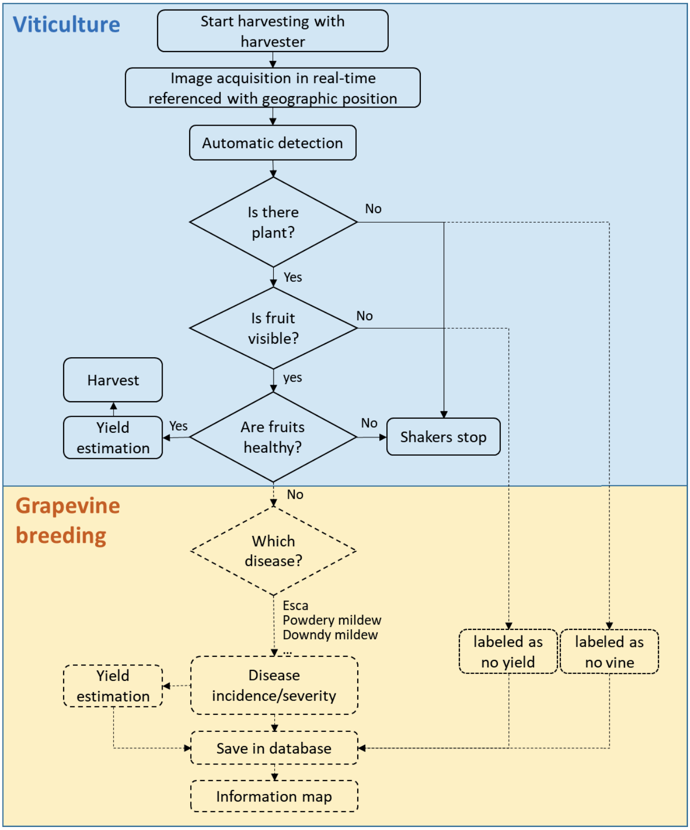

Figure 4.1: Phenotyping pipeline for grape growers and breeders during harvesting. Dotted frames and lines are considered by grape breeders only.

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