COMPUTER VISION-BASED MAPPING OF GRAPEVINE VIGOR VARIABILITY FOR ENHANCED FERTILIZATION STRATEGIES THROUGH INTELLIGENT PRUNING ESTIMATION

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1. INTRODUCTION

The objective of this study is to develop an affordable and non-invasive method using computer vision to estimate pruning weight in commercial vineyards. The study aims to enable controlled fertilization by leveraging pruning data as an indicator of plant vigor [1]. The methodology entails the analysis of RGB and DEPTH images acquired through an embedded platform (Figure 1) in a vineyard cultivating corvina grapes using the guyot method [2].

Figure 1 Embedded vision system

Initially, pruning weight was evaluated by processing pictures taken manually with a controlled background. Then, we developed an algorithm to estimate pruned wood weight based on these images. Subsequently, a mobile sensor platform was utilized to automatically capture grapevine images without a controlled background. Collected data will then be used to deploy a convolutional neural network (CNN) for intelligent pruning estimation capable of extracting meaningful data from real-world environments. Additionally, we integrated and validated a visual-odometry sensor (Intel Realsense T265) to map the spatial variability of pruning estimation results.

2. EXPERIMENTAL SETUP

A series of experimental sessions were conducted. Data collection took place in winter, before pruning, allowing for the presence of numerous vine shoots resulting from the previous spring and summer's vegetative phase.

The Masi Agricola winery generously provided us access to a vineyard dedicated to corvina grapes cultivated using the guyot method [2] for Amarone production. Data acquisition was conducted during daylight hours, encompassing various ambient lighting conditions. The objective of this initial experimental campaign was to characterize the performance of RGB and depth cameras. Without using AI segmentation algorithms, our initial goal was to extrapolate meaningful pixels from the vineyard surroundings. To achieve this, a background-free setup (white sheets were positioned behind the vine) was designed to acquire images of the plants that were close to the camera (figure 2).

This experimental setup enables easy segmentation of vine images using computer vision algorithms, resulting in the extraction of relevant pixels. During the experimental sessions, data were collected simultaneously from multiple sensors. The sensors setup included three cameras: (i) a RGB camera D435i, (ii) an IR depth camera D435i, and (iii) an odometry camera T265. To ensure a high frame rate and minimize motion blur, an NVIDIA Jetson Nano was used as the acquisition device. The Jetson Nano, with its multi-processing libraries and dedicated video card, enabled the simultaneous processing of multiple camera streams. Additionally, this GPU-based device offers the advantage of low power consumption and can be powered by a battery. This configuration was intentionally chosen to allow the integration with a commercial tractor, enabling an exhaustive evaluation of the whole vineyard without additional human involvement.

Figure 2 Experimental setup

3. METHODS

To manage the inherent variability of the plant's woody ramifications, our system models the vine shoots as a series of cylinders with different diameters. Each volume will be measured from its length and diameter. To achieve good measurement accuracy, however, we cannot use 3D point clouds to estimate shoots diameter directly because the resolution of the sensor does not provide good confidence in measurements below 15 mm at 1 m distance [3]. However, we chose this sensor for its ability to be integrated into a low-power embedded device and for its robustness to infrared radiation in the outdoors [4].

To overcome the noise and low resolution of point clouds, we rely on RGB information to accurately measure the dimensions of the vine shoots. To convert the measurements of each cylinder from pixels to the metric system, we need to determine the pixel dimension (i.e. the ratio between millimeters and pixels). This variable is directly influenced by the distance between the object and the camera. When a point cloud is unreliable and contains propagated errors from noise and low resolution, the depth information, taken separately and in clusters, proves to be reliable and consistent. Moreover, data were firstly preprocessed to remove outlier points. By conducting an experimental campaign that involves capturing videos of known volumes at various distances, we can establish a relationship between pixel length and depth. This enables us to estimate a function that converts pixel measurements to millimeters (Figure 3; RMSE = 0.0045 mm/px, R: pixel length, m: regression slope, b: intercept).

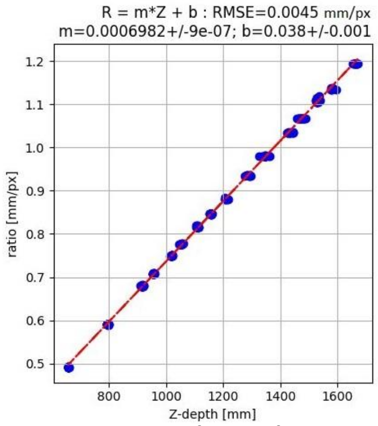

Figure 3 Regression function from camera calibration. Ratio's model w.r.t. Depth data.

Once the camera model was established, we proceeded to measure real vine shoots. To account the intrinsic variability of branch sections, we explored different approaches. The results from multiple acquisitions of a vine sample are shown in figure 4. For shoot length estimation, we obtained a RMSE of 9.2 mm (2.7%) and a mean deviation of 6.3 mm (1.3%). These measurements were taken at distances ranging from 500 mm to 1500 mm. The accompanying histogram (figure 4A) shows the normal distribution of the errors with respect to the actual dimensions. As expected, the deviation increases as the distance from the camera increases (Figure 4B). Our study involves testing various approaches to identify and classify the diameter variability within the same branch. We will apply this same model to perform these measurements. The developed methodology can effectively estimate vine pruning weight and vine shoot dimensions, providing insights into plant vigor [5]. This information can be utilized for precise and targeted fertilization, allowing tailored nutrient application in different vineyard areas.

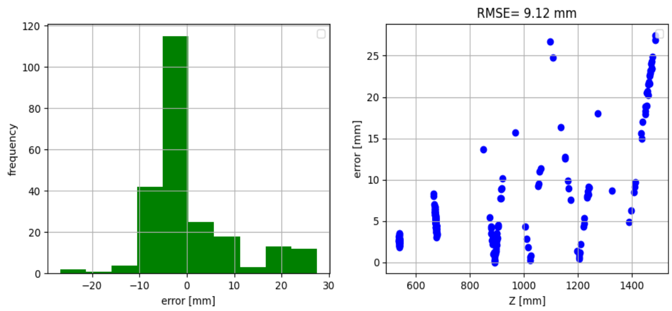

Figure 2 Results and RMSE from vine shoots measurements, Histogram (A) and error w.r.t. depth (B)

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