

# A Robot Platform for Hyperspectral Imaging Applications in Smart Viticulture

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**Abstract**—Hyperspectral imaging is a trending technology in recent years. The growing interest in this technology is due to the richer information that spectral data carries compared to classic RGB imaging. To study the potential of this technology for Smart Viticulture, we have built a robotic platform equipped with three hyperspectral cameras and other classical sensors used in autonomous mobile robotics to collect data in an experimental vineyard and at a commercial vineyard. This data is targeted to grape bunches counting and volume estimation, thus computing yield predictions. The ongoing experimentation aims to use hyperspectral images to estimate the sugar and anthocyanin grape concentration and detect leaves exposed to biotic/abiotic stresses.

**Index Terms**—hyperspectral imaging, smart agriculture, viticulture, artificial intelligence, mobile robotics

## I. INTRODUCTION

Digital technologies are promising tools to make agricultural practices more efficient and to reach the 17 sustainability goals of the United Nations by 2030 [1]. In the context of viticulture, robots are used to automatize many tasks and they can improve productivity by supporting the decision-making process of farmers and agronomists. We can find many examples of smart viticulture applications in the literature, from counting bunches through Deep Neural Networks [2], to automatic pruning with a robot [3].

In recent years, hyperspectral imaging is a new trending topic just appeared in the Smart Agriculture literature [4]. Hyperspectral cameras capture light in many wavelengths beyond the usual red, green, and blue ones. With hyperspectral imaging, richer information can be captured from the scanned object as the reflected radiation also depends on the physical and chemical properties of the object itself. By sampling both the spatial and spectral domains, hyperspectral cameras produce the so-called data cubes. Data cubes are rich in information not present in the common RGB images and can be exploited to give agronomists quantitative evidence upon which they can decide. Indeed, by measuring the physical and chemical properties of plant organs, the use of hyperspectral cameras can avoid costly, laborious, and destructive biological and chemical analyses [5].

The hyperspectral imaging research field is still in its infancy, but it has been foreseen as a breakthrough innovation for the future [6]. For instance, authors of [7] used a hyperspectral camera to estimate the berry soluble solids and anthocyanin

concentration of grapes. They mounted a line-scan hyperspectral camera on a rover to scan entire vineyard rows. Then, they segmented images by exploiting the spectral signatures of grapes to differentiate them from the leaves. Finally, they found a correlation between the chemical parameters and spectral reflectance. Another application of hyperspectral imaging is explained in [8] where the authors wanted to early detect vineyard viral diseases using hyperspectral images and Deep Learning. In that case, they used a snapshot camera mounted on a static tripod to collect pictures of diseased leaves. Then, they analyzed the images with Deep Learning algorithms to discriminate between the spectral signatures of healthy and diseased leaves.

Besides this interest in hyperspectral data, little if any public dataset is available for research. For these reasons, we have built a robotic platform equipped with different hyperspectral cameras (and other sensors) to scan vineyard plants and collect datasets aimed at estimating yield, bunch volume, sugar and anthocyanin grape concentration, and to detect leaves subjected to biotic/abiotic stresses.

## II. HYPERSPECTRAL DATA COLLECTION PLATFORM

Even if our research focuses on hyperspectral sensors and the analysis of the multidimensional data they generate, other information is needed to extract value from spectral data in a close range scenario, e.g., to reconstruct a large scale representation by merging several close-range views. Thus, we built a data collection platform based on a four-wheeled skid-steering robot and a sensor suite mounted on it. The sensors we adopted are three hyperspectral cameras (a Senop HSC-2 camera and two Ximea cameras), two LiDAR sensors (a 2D Sick LMS100, and a 3D 64 planes Ouster OS-1), two RGB-D cameras (Intel Realsense D435), a GPS receiver (Emlid Reach M2), three IMUs (a 3DR Pixhawk Mini, and other two IMUs embedded in the camera and LiDAR), and a tracking vision system (Intel Realsense T265). The hyperspectral cameras are used to estimate some plants parameters like grape maturity and the presence of diseases. The LiDAR sensors are employed with the Realsense D435 cameras to build a tridimensional reconstruction of the rows. The GPS receiver, the IMU sensors, and the Realsense T265 camera information are fused to obtain an accurate robot localization. Since our present goal is data collection, this robot has been teleoperated



(a) Experimental vineyard (b) Commercial vineyard

Fig. 1: Robot platform in two different experimental settings.

along vineyard rows to collect rich multi-sensor datasets. In particular, we have collected data at two different sites with multiple purposes.

The first site is an experimental vineyard at the Università Cattolica del Sacro Cuore di Piacenza. In this setting, we had two rows of plants accounting for 25 plants in total. Plants were in a controlled outdoor environment, planted in pots and on a flat cement floor, as can be seen from Figure 1 (a). Plants have been divided into two groups to test the effect of a modified crop load (bunch thinning vs. control) on grape growth and maturity. From pre-veraison to harvest, five surveys have been planned. During each survey, plants have been scanned with the sensors mounted on the robot. We aim to analyze the data with Deep Learning algorithms to detect the single bunches and estimate their volume, thus giving a yield prediction that farmers can exploit to better plan the harvest activities. Also, we aim to detect the sugar and anthocyanin grapes content with hyperspectral cameras and build machine learning models estimating the grapes' maturity state. In particular, we highlight the availability of ground truth data consisting of laboratory physical and chemical analyses.

The second site of our experiments was an organic commercial vineyard sited in Pianello Val Tidone (PC, Italy). The vineyard consisted of rows of different lengths, with the longest of about 200 m and the shorter of about 100 m. In this vineyard, we thoroughly scanned with the sensors mounted on the robot four rows. This activity aims at estimating the canopy volume of vine plants that is a piece of useful information correlated to the plant productivity and vineyard management. Ground truth data will be provided in this case by manual physical measures with agronomic tools. In the same vineyard, we also scanned with hyperspectral cameras a part of a row where symptomatic leaves were present together with healthy plants. The aim is to predict the disease outbreak before it is visible since a modification of the leaves' chemical properties (and thus of the reflected radiation) is already in place in the early stages of the disease. Figure 1 (b) shows our robot in

the commercial vineyard of this second setting.

### III. ONGOING AND FUTURE ACTIVITIES

We are currently exploiting Artificial Intelligence (AI) algorithms to analyze the collected data. RGB images are going to be segmented to detect bunches and grapes, and then, a relation will be extracted between pixel area and measured ground truth volume. Depth measure from the RGB-D cameras or point clouds extracted by LiDAR sensors can also be exploited to have greater accuracy. Once the season is over, it will be possible to develop a model predicting the final yield starting from data collected at the beginning and during the season. Hyperspectral images will also be used to derive a relationship between the fruit composition (i.e. total soluble solids and anthocyanins) and the grape spectral signature. Regarding the datasets collected in the commercial vineyard, LiDAR information will be used to reconstruct the plant canopy and compute its volume and hyperspectral images will be used to distinguish healthy from diseased.

Despite its potential benefits, the analysis of hyperspectral data poses some challenges. Indeed, the amount of information associated to the hyperspectral acquisition comes at the cost of an increased computational effort to elaborate them. A critical point to solve is developing a hyperspectral data handling pipeline to manage hyperspectral data complexity and make this tool effective in supporting farmers and agronomists.

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