Vineyard monitoring using an autonomous ground robot embedding multispectral imaging, LiDAR and 5G communication for edge computing

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Abstract

A robotic vineyard monitoring system embedding high resolution and data intensive sensors was designed. The rationale of the design is to exploit the communication capabilities of 5G technologies in order to use edge computing for analysing data. The monitoring system includes both a robot with multispectral imaging and 3D LiDAR and a network of field sensors. An experiment was set to test the monitoring system in a commercial Cabernet Sauvignon vineyard in the province of Toledo. The monitoring was made on 50 vines on which 5 contrasted means of managing the canopy and its growth were implemented. Physiological parameters of the vine were also recorded, and data on the quantity and quality of grapes were acquired. Preliminary results show that it is possible to extract parameters from the database that allow the evolution of the crop to be followed, obtaining relevant information to support the winery's decision-making regarding the management of agricultural inputs.

Keywords: sensors, robotics, camera, lidar, crop modelling, real-time data

Introduction

Since the introduction of sensors and information and telecommunication technologies in the agricultural sector, vineyard monitoring has been a mainstream in advanced agriculture, mainly due to the high end-value of the product and the use of technology this crop (Barriguinha et al., 2021). The number of publications relating to precision viticulture corresponds to 5 % of the publications relating to precision agriculture (Ferro & Catania, 2023). A key objective of using these technologies is to obtain and supply data to grape growers and wine producers as a basis for improving land and vine management through a more-informed decision-making process, recently with the aid of artificial intelligence modelling (Tardáguila et al., 2021). Among the variety of technologies, proximal sensing has been widely developed (Moreno & Andújar, 2023), and also robotics for crop scouting and data acquisition (Botta et al., 2022; Roure et al., 2020). The vast amount of data generated by these sensors could benefit from last generation communication technologies such as 5G mobile networks and edge computing. Only recent projects have explored this path (Edemetti et al., 2022). Previous research lack of an integrated approach combining data intensive sensors, wireless plant monitoring, fast communications and edge computing for real time data collection and modelling. This aim of this work is developing a case study through the implementation of a robotic prototype for vineyard phenotyping with onboard sensors combined with field sensors, working in collaboration with a specifically deployed 5G network for real time database sending and cloud computing. The working hypothesis is that the combination of data will allow estimation and forecasting of crop evolution and final harvest.

Design of the acquisition systems used at the vineyard

Multiple systems have been used to monitor the vineyard: a mobile robotic system with onboard sensors, a set of field sensors at the vines, and the data communication system to the cloud computer. The mobile robotic unit is composed of two subsystems: mobile platform and robotic manipulator. Selected mobile robotic platform is the Summit XL (Robotnik, Spain), due to its robustness, reliability for navigation and versatility to overcome uneven terrain outdoors with vegetation and dirt, with a payload of 50 kg. Regarding the robotic manipulator, the Unitree Z1 Pro (Unitree, HongKong) was selected for data acquisition tasks in the vineyard due to its nominal reach of 740mm and payload of 3 kg, suitable for the sensors located on the end effector. According to the data acquisition needs, the system is sized for an autonomy of 2.5 hours. Figure 1 shows hardware architecture and figure 2 depicts the final field acquisition system.
Framework: equipment was integrated under the robotic operating system (ROS) in the on-board computer, using Ubuntu 20.04, ROS Noetic.
Onboard sensors for navigation include: a 3D LiDAR VLP-16 (Velodyne, USA), with a 360º horizontal field of view and 40º vertical field, a range of 200m, 16-channel resolution, 20Hz frequency and precision of +/- 3cm. For localization, a C099-F9P-1 module (Ublox, Switzerland) with a GPS-RTK ZED F9P is integrated. Sensor fusion was carried out by an inertial measurement unit (IMU), GPS-RTK, wheel odometry and odometry estimation based on one channel of the Velodyne LiDAR.
Onboard sensors for crop monitoring: an Altum (MicaSense, USA) multispectral camera originally designed for integration with drones and other aerial platforms was mounted on the grip of a robotic arm to record images of each plant at an approximate distance of 0.6 m from the vine, capturing both sides of the vegetation. The camera collects data across five distinct spectral bands: blue (475 nm), green (560 nm), red (668 nm), red-edge (717 nm), and near-infrared (842 nm), with bandwidths of 20 nm for the blue and green channels, 10 nm for the red and red-edge channels, and 40 nm for the near-infrared channel. Each of the camera sensors offer a resolution of 2064 x 1544 pixels with a pixel size of 3.45 µm. Analysis of multispectral images served two objectives depending on the phenological stage of the plants: 1) leaf density estimation as a predictor of potential

yield; 2) identification of grape clusters on each vine, enabling the generation of yield maps with plant-level resolution. Note that this spatial resolution is challenging to achieve with systems based on load cells installed on harvesting machines. At the tip of the manipulator a 2D LiDAR system (URG-04LX, Hokuyo, Japan) was programmed to record the point cloud (PC) vertically and horizontally at each vine, for 3D reconstruction. Hardware architecture is shown on Figure 1, and field experiments on Figure 2.

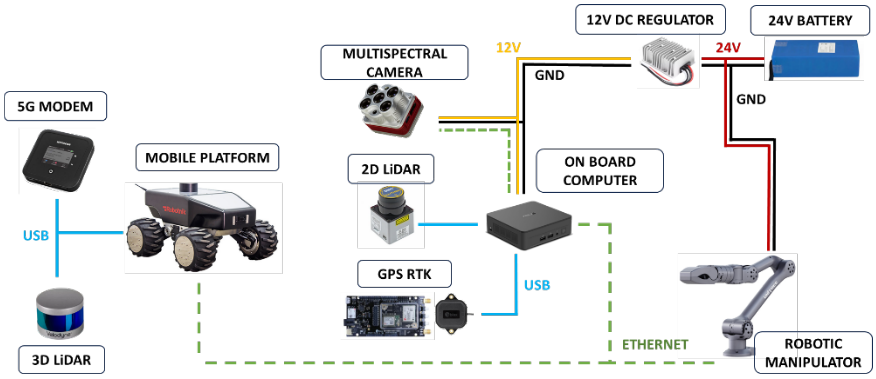

Figure 1. Hardware architecture of the system for power and communications

Figure 2. Data acquisition on field experiments

A wireless sensor system for weather and soil monitoring was installed in the field, consisting of a local weather station (Plantae, Spain) and eight soil sensors installed at two depths (10 & 20 cm), to monitor the four different treatments delineated in the vineyard (see ahead).

Communication system: the connection to Telefónica's 5th generation mobile network was achieved through a 5G router with a terrestrial connection transmitting real time data as acquired by the robotic system. To achieve good performance of the mobile network, a 5G antenna has been deployed in the 700 MHz band in an area close to 'Bodegas y Viñedos Casa del Valle' estate (Yepes, Toledo). The location of the 5G public network antenna that serves the estate is almost 2 km from the winery with direct vision. On top of that, the connection through a satellite network, based on low-Earth orbit (LEO) and geo-synchronous orbit (GEO) constellations, has also been tested punctually as backup.

Field experiment design and registration of physiological parameters

The study was conducted on a plot of 4 ha in a commercial Cabernet *Vitis vinifera* L. over Selection Oppenheim 4 (SO4) rootstock vineyard located in 'Bodegas y Viñedos Casa

del Valle' in Yepes (39°56'26.2" N, 3°42'49.7" W), Spain, at 699 masl during the 2024 season. The vineyard was planted in 2002 with a plantation frame of 2.6 x 1.1 m. Plants have been trained in a double cordon system and arranged on a trellis. Treatments were designed with the objective of achieving variability in the canopy structure. To this end, selective removal of shoots and leaves (defoliation) was carried out, applying these practices at varying percentages depending on the specific treatment goals. Additionally, lower canopy trimming was performed to prevent shoots from extending into the row. This approach allowed for controlled modulation of the canopy architecture, targeting differences in light exposure, ventilation, and microclimatic conditions within the canopy. By incorporating these methods, the study aimed to explore their influence on physiological responses, fruit quality, and overall vine performance. For data acquisition, 5 consecutive canopy vineyard treatments comprising 10 adjacent vines each (50 vines in total) were labeled. Treatment 1 (T1): 50% leaves removed, Treatment 2 (T2): 25% leaves removed, Treatment 3 (T3 reference treatment): Light shoot tipping, Treatment 4 (T4): 50% shoots removed and Treatment 5 (T5): 25% shoots removed.
Stem water potential (SWP) was measured (MPa) on 9 dates: 29thMay, 5&19June, 3,17&31July, 14& 28Aug, 02Sept with a Scholander-type pressure chamber (Soil Moisture Equipment Corp., Santa Barbara, CA, USA), stomatal conductance utilizing a steady-state leaf porometer (SC-1, Decagon Devices, WA, USA) and chlorophyll content in leaves (µmol chlorophyll/m2 leaf area) with a MC-100 sensor (Apogee Instruments Inc., Logan, UT, USA); the three measurements were taken immediately after robot scan. Canopy characteristics were estimated using point quadrat analysis (PQA) reference measurements on 28/05/2024, 05/06/2024, 19/06/2024, 03/07/2024. Also canopy height and width were recorded, and canopy volume derived. In each horizontal interval, canopy width was noted at three heights (90, 120, and 150 cm from the ground)
Production and quality: experimental vines were harvested by hand (02/09/2024). Bunches were counted and weighed. Between 150 and 200 berries were selected for subsequent analysis to determine the total soluble solids (◦Brix) and pH.

Results and discussion

The robotic system interface includes two windows, corresponding to robot navigation (path planning and static and dynamic obstacle avoidance) and data acquisition. The data acquisition stage consists of the 3D reconstruction of the vine and the acquisition of multispectral images. This interface is shown in Figure 4. For the estimation of leaf density, the red-edge channel was found out to provide higher contrast in canopy pixels, likely due to its capacity to penetrate plant tissues, revealing underlying leaves. Higher grayscale values correspond to areas with fewer successive leaf layers, leading to differences
To quantify these differences in the histograms an index defined as the inverse of the intensity values, and hereafter referred to as DGI, was calculated. The sum of the DGI values provides an indication of the amount of foliage in the image. This summation accounts for both the number of pixels and a weighted value that gives greater importance to more shaded pixels, which likely correspond to areas with more overlapping leaves

(higher leaf density). Figure 5 shows examples of red-edge images and their corresponding virtual DGI images alongside the histograms of two vines with different leaf densities. Ongoing analyses aim to determine whether the total DGI sum in the images allows differentiation between vines of varying leaf density and whether it correlates with their subsequent yield. in the histograms based on leaf density.

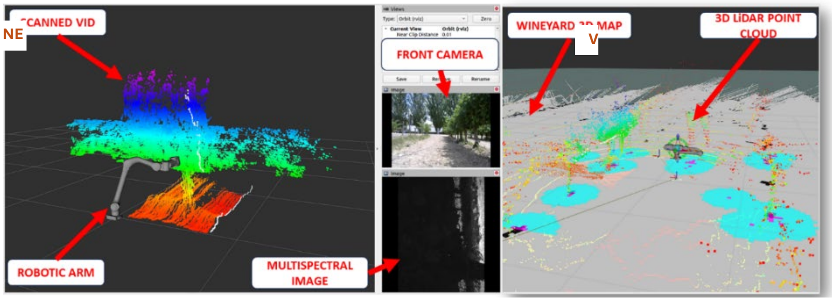

Figure 4. Visualization interface for robot navigation and data acquisition

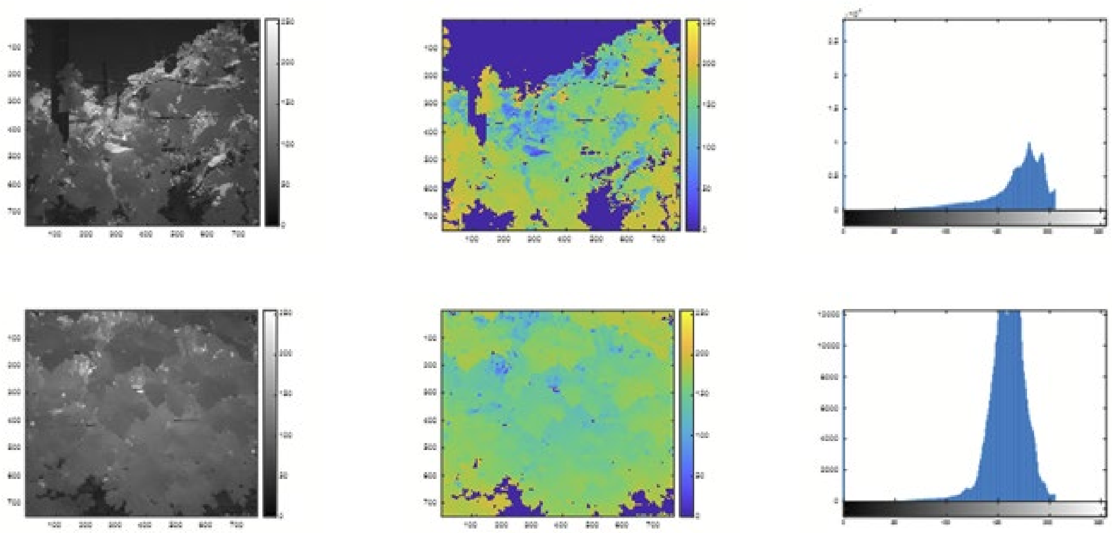

Figure 5. Red-edge images of vines with low (up) and high leaf density (down) and its corresponding virtual images and histograms of DGI

The identification of grape clusters required the registration of images from the R, G, and B channels to generate a colour image, which necessitated the adaptation of routines for identifying homologous pixels across the three-channel images. The short distance between the vehicle and the vegetation causes the area captured in each channel's image to differ significantly, complicating the process of channel registration and concatenation. To address this, the maximization of the mutual information method was implemented in Matlab, and the quantification of grape pixels in each color image was performed through thresholding in different color spaces. For leaf reflectance estimation through computer vision techniques, an area of interest was cut out, a mask was applied to remove the background, and the average of the pixel intensity values for the image was estimated, obtaining a value for each channel (Fig. 6).

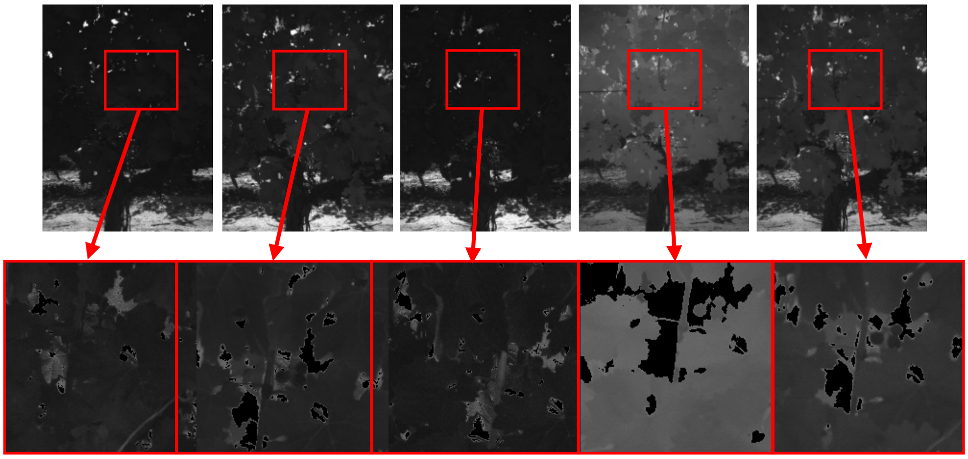

Figure 6. Masking and filtering of channel RGB, red-edge and NIR for reflectance estimation

Estimation of leaf volume is carried out through the generation of alpha shapes, generalizing concave polygons that contain sets of points. For this, PC recorded by the tip LiDAR were filtered by eliminating outliers, down sampled to voxels, trimming the area corresponding to the leaves, and estimating the volume of the polyhedron (Fig. 7).

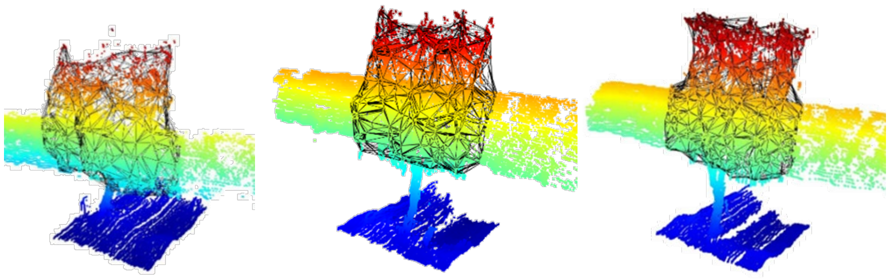

Figure 7. Examples of leaf volumetric estimation through alpha shape polyhedron.

All the data collected by the robot, the station and the sensors were sent continuously to a Telefónica server hosted in the nearby cloud, or edge computing, through 5G connectivity in the 700 MHz band. This type of architecture allows the computing capabilities of the network to be brought closer, avoiding the installation of on-premise infrastructure, which in a rural area can be complicated. On this server, the data will be processed using advanced analytics to obtain a machine learning model capable of predicting the results of the following campaign. In addition, the 700 MHz frequency (low band) provides a wide coverage footprint, which is why it is used in less densely populated areas or rural areas. This is demonstrated by the quality checks, both of coverage and bandwidth, throughout the entire route of the robot through the area of the vineyard under study, which have been positive. Likewise, satellite connections have been tested for data transmission with good results.

A Support Vector Regression (SVR) model was implemented in Matlab, incorporating key variables such as the percentage of grape bunch area, plant leaf volume, and actual yield. This approach allows for more accurate yield predictions by leveraging plant structural parameters. The SVR model demonstrated a prediction accuracy of 63% ($R^2 = 0.63$) (Fig. 8a), suggesting that while it captures a significant portion of the variance, further optimization is required to enhance its predictive capability.

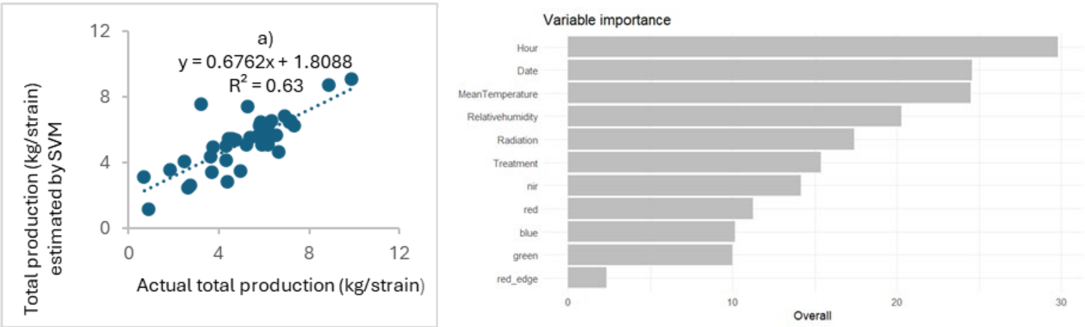

Figure 8 a) Grape harvest prediction using SVM, b) Importance variable in RF model

Additionally, a Random Forest (RF) regression model was developed to estimate Stem Water Potential (SWP) based on mean temperature (°C), relative humidity (%), radiation (MJ/m^2), and multispectral data (red, blue, green, red-edge, and NIR bands) captured by the robot. RF model output (Fig 8b) defines greater importance of meteorological features. Specifically, mean temperature and relative humidity were significant contributors to the model. These results align with the findings of Tang et al. (2022) and Berry et al. (2023), who emphasized the importance of integrating meteorological and spectral data for precise SWP estimation.

Conclusions

An automatic data acquisition system has been designed and implemented for registration of images and point clouds, along with field sensors. Data analysis performed so far shows promising results both for reconstruction of canopy volume and for yield estimation. Providing a communications and cloud computing (in this case edge computing) infrastructure is essential to ensure the capture, sending and processing of data that allows the development of new use cases for smart agriculture. One of the strong points of this project is the use of deployed 5G network in rural areas in the 700 MHz frequency. The network was capable of transmitting data in real time at speeds much higher than previous generations of mobile telephony, as the files sent by the robot are some GBs in size. End users can have real-time, historical data and prediction models that help them make data-based decisions and apply precision viticulture.

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