Mobile Robotics and Autonomous Mapping: Technology for a more Sustainable Agriculture

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Fig. 1 - The mobile robot traversing under the canopy in a maize field (Manish et al., 2022).

Today, food systems account for nearly onethird of global greenhouse gas emissions, consume large amounts of natural resources and are among the causes of biodiversity loss.

As part of the actions of the European Green Deal, the Farm to Fork Strategy (European Commission, 2020) plays therefore a crucial role to reach the ambitious goal of making Europe a climate-neutral continent by 2050. In fact, it aims to accelerate the transition towards a sustainable food system, reducing dependency on pesticides, decreasing excess fertilization and protecting land, soil, water, air, plant and animal health. All actors of the food chain need to contribute to the implementation of this strategy, starting from the transformation of production methods that can benefit from novel technological and digital solutions to deliver better environmental and climate results.

In this context, we are witnessing an increasing demand for automated solutions to monitor and inspect crops and canopies, that are driving the adoption of autonomous and robotic systems with computational and logical capabilities. The introduction of robotics and automation, coupled with Geomatics techniques, could provide notable benefits not only in terms of crop production and land use optimization, but also to reduce the use of chemical pesticides, improving sustainability and climate performance through a more results-oriented model, based on the use of updated data and analyses. For these reasons, the implementation of autonomous and robotic solutions together with advanced monitoring techniques is becoming of paramount importance in view of a resilient and sustainable agriculture.

Applications of mobile robotics in agriculture span from a large variety of tasks, as for instance, harvesting, monitoring, phenotyping, sowing, and weeding. A particular task in which mobile robots are currently employed at a faster pace than in previous years is 3D mapping, as testified by a flourishing literature on the topic (Tiozzo Fasiolo et al., 2022). Indeed, 3D maps of agricultural crops can provide valuable information about the health, stress, presence of diseases, as well as morphological and biochemical characteristics. Furthermore, 3D surveys of plants and crops are fundamental in the computation of geometrical information, such as volume and height, to be used to reduce pesticide and fertilizer waste and water usage, and, therefore, improve sustainability and environmental impact.

Obviously, to provide useful information for crop management and to perform the survey in the most automatic way possible, robotics platforms must be equipped with appropriate technology. In the following, we will therefore try to summarize trends and future developments

in this domain.
The first requirement of mobile robots in agriculture applications is the availability of onboard sensors and computational capabilities. Common sensors are 2D and 3D LiDAR (Light Detection and Ranging), cameras (monocular, stereo, RGB-D, and time-of-flight ones), as well as RTK-GNSS (Real-Time Kinematics Global Navigation Satellite System) receivers, and IMUs (Inertial Measurement Units), the latter two used mainly for localization tasks.
Among the robotic systems recently proposed in the literature for 3D mapping in agriculture, it is worth mentioning the platform developed in (Manish et al., 2021) and shown in Figure 1. That system is capable of collaborating with a drone to build a dense point cloud of the field. Another interesting mobile robot is BoniRob (Figure 2), developed by Bosch Deepfield® Robotics (Chebrolu et al., 2017). It is an omnidirectional robot and carries a multispectral camera, able to register four spectral bands, and an RGB-D sensor to capture high-resolution radiometric data about the inspected plantation. Multiple LiDAR sensors and GNSS receivers as well as wheel encoders provide at the same time observations employed for localization, navigation, and mapping. An example of robot with an onboard manipulator is given by BrambleBee (Ohi et al., 2018). That robotic system features a custom end effector designed to pollinating flowers in a greenhouse.
Images from standard RGB cameras only supply information about the plants in the visible spectrum. To investigate vegetation indexes related to the crop vigor, as for instance the NDVI (Normalized Difference Vegetation Index), multispectral and hyperspectral sensors are needed, which can measure the near infrared radiation reflected by the vegetation leaves. However, only a paucity of robotic platforms described in the literature manage to perform this task.
The mobile lab developed at the Free University of Bolzano and shown in Figure 3 is among them (Bietresato et al., 2016).
A prototype of mobile robot for 3D mapping in agriculture is currently being developed at the University of Udine, based on an Agile-X Robotics Scout 2.0 platform (Figure 4). The robot can navigate in harsh terrain and narrow passages thanks to its four-wheel drive and differential kinematics. The platform is equipped with a low-cost GNSS receiver and a 9-degree-of-freedom (DOF) IMU as direct georeferencing systems. Moreover, it features a great computational capability thanks to the NVIDIA Jetson AGX Xavier board, developed to exploit artificial intelligence (AI) algorithms even in embedded systems. The perception of the environment is guaranteed by a rotating 360° LiDAR and an RGB-D camera. Finally, for phenotyping purposes it exploits a multispectral camera pointing forward to acquire information on the near infrared and the red edge portion of the light spectrum.
As far as the sensorial and computational capabilities are

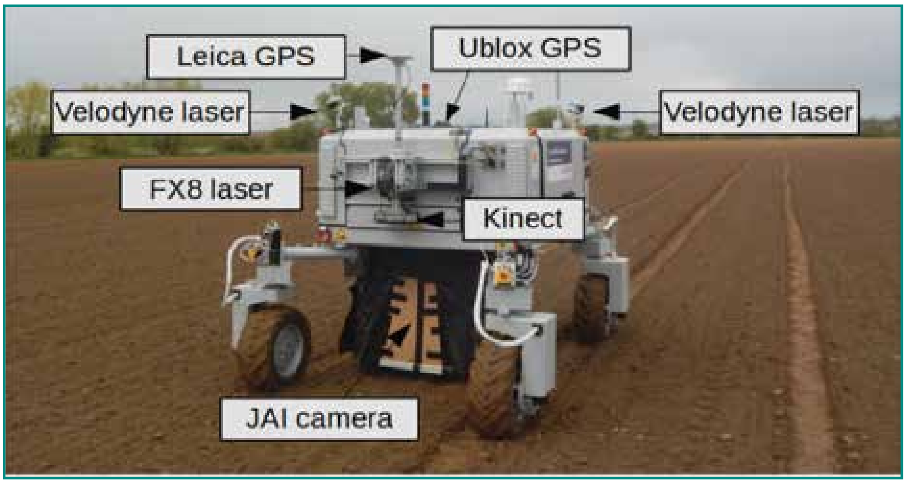

Fig. 2 - Agricultural field robot BoniRob with onboard sensors (Chebrolu et al., 2017).

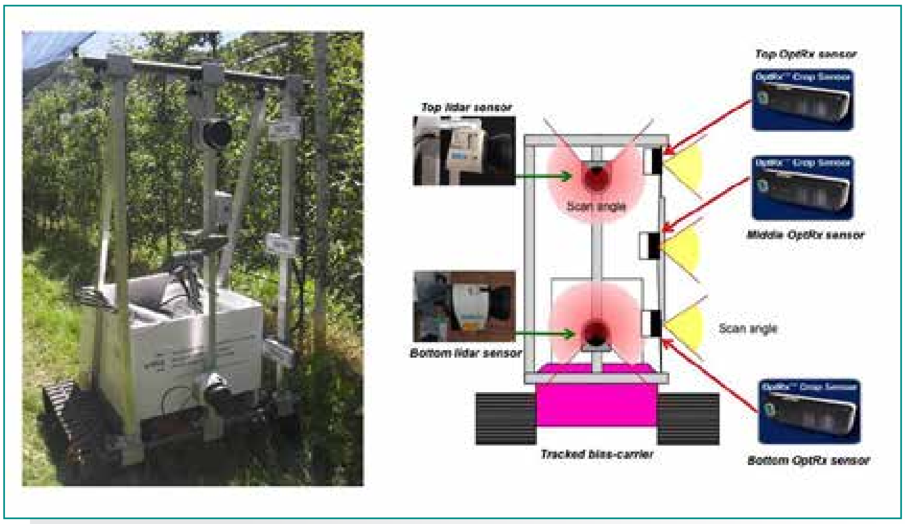

Fig. 3 - Agricultural robot developed at the Free University of Bolzano, Italy: robot in a orchard, and onboard sensors (Bietresato et al., 2016).

Fig. 4 - The sensorized mobile platform developed at University of Udine, Italy.

considered, from the literature it can be noticed that most of the robotic platforms operating in the agricultural environment usually employ physical devices to store the acquired data, whose can require a frequent manual intervention of an operator. The implementation on Internet of Things (IoT) approaches, together with the storage of data on clouds could be a great improvement, making data remotely available. Future improvements in this context will also include the integration of renewable energy sources, such as solar panels, to increase the autonomy of the systems, especially in large scale operations (e.g., autonomous 3D mapping of a whole vineyard). Moreover, to avoid occlusion problems that can occur in image-based phenotyping, sensors can be mounted on a robotic arm that can optimize the camera pose, guaranteeing the best point of view for data acquisition. However, it should also be underlined that eye-in-hand configurations for LiDAR sensors and multispectral cameras are not exploited yet. A further important aspect is the durability of these systems and sensors, that should be designed to operate in severe outdoor scenarios.

Fig. 5 - Person following with YOLO object detection (Masuzawa et al., 2017).

To navigate autonomously in the surrounding environment, a mobile robot needs a robust localization method that can georeference the data acquired by means of the onboard sensors. Direct georeferencing methods are usually based on the RTK-GNSS, that provides position at low update rate, generally coupled with a 9-DOF IMU, which however is sensible to noise in rough terrains. Higher accuracy for the localization of the robot and the generated 3D map can be achieved using in addition Simultaneous Localization and Mapping (SLAM) approaches. As well-known also in the Geomatics community, SLAM problem consists in the estimation of the pose of the robot/sensor, while simultaneously building a map of the environment. State-of-the-art methods are divided into two main groups: visual SLAM and LiDAR SLAM. The former approach relies on images and sequentially estimates the camera poses by tracking keypoints in the image sequence. The popular approach for LiDAR SLAM is instead based on scan matching: the pose is retrieved by matching the newly acquired point cloud with the previously built map, which is constantly updated as soon as new observations are available. Although not yet fully implemented in mobile robots for precision agriculture applications, an optimal solution could be data fusion, taking the advantages of both visual and LiDAR SLAM methods. In addition, since external conditions can significantly vary among different application and the environment dictates the most advantageous sensor, the robot itself should be able to choose and use the most suited data source according to the environmental conditions. Many open-source SLAM algo-

rithms are currently available, that can run in real time or in post-processing mode. To this regard, a comparison among the state-of-the-art SLAM algorithms could be interesting, together with a quantitative evaluation of the obtained 3D maps performed with respect to ground truth datasets. Conversely, there is a lack of methods to efficiently fuse spectral data acquired by multispectral and hyperspectral cameras with LiDAR point clouds, fundamental for agriculture applications.
Another important aspect that must be considered for the profitably application of mobile platforms is the autonomous navigation ability, guaranteed by path planning algorithms. Path planning is a mature field in mobile robotics, and, in the crop monitoring context, it generally consists of providing a global path to map an entire area. This approach is called coverage path planning and is usually coupled with a row-following algorithm to provide local velocity command to the robot.
A recent trend in the coverage path planning is the development of algorithms that avoid repetitive paths to minimize soil compaction. This approach generally relies on prior information of the working area, that could be acquired thanks to the collaboration with drones, useful to capture an up-to-date 2D or 3D model of the environment. Furthermore, a promising solution could be extending the range of action with swarm robotics, that is the collaboration of several unmanned ground vehicles (UGVs).
Nowadays, another fundamental aid for agricultural applications based on mobile robotics is given by artificial intelligence (AI). In fact, classification and segmentation algorithms of images and point clouds based on AI are increasingly used to enrich the 3D map with semantic information, also in real time. This is possible mostly thanks to the advances in the computational performance of modern embedded computers that can be installed onboard a mobile platform.
For instance, a convolutional neural network (CNN) applied to the acquired images can provide bounding boxes of objects of interest, that can constitute the basis to build a topological map with key location estimation and semantic information. This is exploitable also to give the robot person following capability, as done in the work by (Masuzawa et al., 2017) (Figure 5). Another example of machine learning application is given by the work in (Reina et al., 2017), which employed a support vector machine to classify the terrain on which the robot is navigating, by means of wheel slip, rolling resistance, vibration response experienced by the mobile platform and visual data. Recent trends in this field also comprise the use of generative adversarial networks to generate photorealistic agricultural images for model training, as well as the recognition of diseases with CNN.
In the coming years we will witness great progress in all the domains highlighted by this work, from sensors to mobile platforms, from localization algorithms to artificial intelligence methods, with the hope that these innovations will effectively contribute to the transition to a more sustainable, healthy and environmentally-friendly food system.

REFERENCES

European Commission (2020). Farm to Fork strategy for a fair, healthy and environmentally-friendly food system. https://ec.europa.eu/food/horizontal-topics/farm-fork-strategy_en
Tiozzo Fasiolo, D., Scalera, L., Maset, E., Gasparetto, A. (2022). Recent Trends in Mobile Robotics for 3D Mapping in Agriculture. In International Conference on Robotics in Alpe-Adria Danube Region (pp. 428-435). Springer, Cham.
Manish, R., Lin, Y. C., Ravi, R., Hasheminasab, S. M., Zhou, T., Habib, A. (2021). Development of a miniaturized mobile mapping system for in-row, under-canopy phenotyping. Remote Sensing, 13(2), 276.
Chebrolu, N., Lottes, P., Schaefer, A., Winterhalter, W., Burgard, W., Stachniss, C. (2017). Agricultural robot dataset for plant classification, localization and mapping on sugar beet fields. The International Journal of Robotics Research, 36(10), 1045-1052.
Ohi, N., Lassak, K., Watson, R., Strader, J., Du, Y., Yang, C., et al. (2018). Design of an autonomous precision pollination robot. In 2018 IEEE/RSJ international conference on intelligent robots and systems (IROS) (pp. 7711-7718). IEEE.
Bietresato, M., Carabin, G., D'Auria, D., Gallo, R., Ristorto, G., Mazzetto, F., Vidoni, R., Gasparetto, A., Scalera, L. (2016). A tracked mobile robotic lab for monitoring the plants volume and health. In 2016 12th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA). IEEE.
Masuzawa, H., Miura, J., Oishi, S. (2017). Development of a mobile robot for harvest support in greenhouse horticulture—Person following and mapping. In 2017 IEEE/SICE International Symposium on System Integration (SII) (pp. 541-546). IEEE.
Reina, G., Milella, A., Galati, R. (2017). Terrain assessment for precision agriculture using vehicle dynamic modelling. Biosystems engineering, 162, 124-139.

KEYWORDS

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ABSTRACT

The introduction of robotics and automation, coupled with Geomatics techniques, could provide notable benefits not only in terms of crop production and land use optimization, but also to reduce the use of chemical pesticides, improving sustainability and climate performance through a more results-oriented model, based on the use of updated data and analyses. For these reasons, the implementation of autonomous and robotic solutions together with advanced monitoring techniques is becoming of paramount importance in view of a resilient and sustainable agriculture.

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