Recent Trends in Mobile Robotics for 3D Mapping in Agriculture

Publisher:
Springer Science and Business Media B.V.

Published
DOI:10.1007/978-3-031-04870-8_50

Recent trends in mobile robotics for 3D mapping in agriculture

Diego Tiozzo Fasiolo[1,2], Lorenzo Scalera[1], Eleonora Maset[1], and Alessandro Gasparetto[1]

[1] University of Udine, Udine, Italy
{lorenzo.scalera, eleonora.maset, alessandro.gasparetto}@uniud.it
[2] University of Naples Federico II, Naples, Italy
diego.tiozzofasiolo@unina.it

Abstract. This article presents trends and future developments in mobile robotics for 3D mapping in agriculture. Recent examples of robotic platforms and sensors are first presented to highlight the technologies adopted for autonomous surveying in the agricultural field. Then, localization and mapping approaches are discussed, as well as path planning algorithms for the navigation of mobile robots in orchards and crops. Finally, insights into applications of artificial intelligence to robotic mapping are given to evaluate the potentiality of neural networks in this field. The results of the survey indicate research directions and suggest future applications of mobile robotics as an efficient tool for smart agriculture.

Keywords: mobile robotics · 3D mapping · precision agriculture · SLAM · path planning · artificial intelligence

1 Introduction

In recent years, mobile robotics has been applied in several different fields to autonomously acquire 3D information for surveying and monitoring. Notable applications include the mapping of hazardous and cluttered areas [13], indoor and outdoor buildings and structures [1,18], as well as archaeological sites [14]. Agriculture is a challenging field in which robotic systems are adopted for various tasks, as for instance, planting, sowing, weeding, harvesting and phenotyping [21]. Their use is expected to boost precision agriculture (PA), with significant advantages in terms of environmental impact of the crop production cycle, as they enhance speed, coverage, repeatability, and cost effectiveness [12].

In this context, mobile robotic platforms (often referred to as unmanned ground vehicles, UGVs) equipped with sensors and computational capabilities are increasingly used for generating 3D maps that provide information about health, number of plants, inflorescence, presence of parasites or diseases, water content as well as chemical and morphological characteristics [4]. More in detail, the near infrared (NIR) radiation reflected by vegetation can be measured by means of multi-spectral cameras, and indexes that provide information to assess the crop health, such as the Normalized Difference Vegetation Index (NDVI)

[11,29], can be computed. Moreover, from a 3D map it is possible to measure volume of plants and canopy height, which are necessary to monitor crop growth, reduce pesticide losses, and make agriculture more efficient and sustainable [24].

To navigate and monitor the environment, robots need to perform online localization and mapping. Positioning based on Global Navigation Satellite System (GNSS) is the most used method for localization in outdoor scenarios and, in particular, in agriculture [2]. However, when satellite signals are unavailable or inaccurate, the simultaneous localization and mapping (SLAM) approach is a promising solutions for localization reliability and availability.

Furthermore, autonomous and safe navigation is one of the hardest challenges in the agricultural context, since agrarian environments are intricate and unstructured [25]. For this reason, path planning strategies commonly used for indoor environments may not fit the agricultural requirements, leading to the necessity of implementing ad-hoc approaches to plan the route of a robot avoiding obstacles and optimizing the required task.

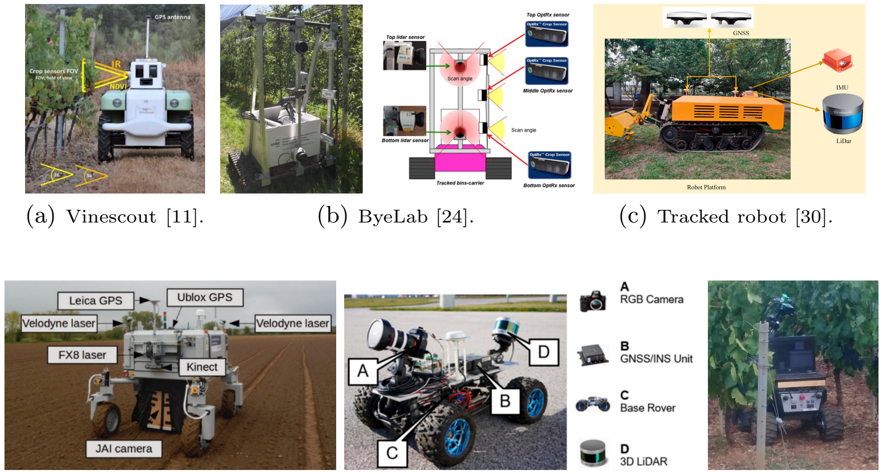
Artificial intelligence (AI) technologies, especially machine learning, are expected to play a relevant role in 3D mapping, and will be essential enablers for agricultural robots [9]. In the mapping context, deep learning methods are investigated for the interpretation of sensor data, recognition, classification and segmentation, especially coupled with vision systems, including depth perception and scanning sensors, such as Light Detection And Ranging (LiDAR).

The main contribution of this paper is a discussion on recent trends and future developments of mobile robotics for 3D mapping in agriculture. Actual examples of robotic platforms are first presented to highlight the technologies adopted for autonomous surveying in agricultural scenarios, with particular focus on the characteristics commonly found in recent agricultural applications (Sect. 2). Then, SLAM approaches are surveyed and compared in Sect. 3. Moreover, insights into path planning strategies (Sect. 4) and applications of AI (Sect. 5) are illustrated. Finally, the conclusions are given in Sect. 6.

2 Robotic platforms and sensors

In the following, recent examples of robotic platforms and sensors are described to outline the state of the art and the research trends for agricultural purposes. UGVs are developed with different kinematics to adapt to the navigation in agricultural harsh terrains: differential wheeled robots [11] (Fig. 1(a)), high-grip tracked vehicles [24] (Fig. 1(b), 1(c)), and solutions with multiple steering wheels [6] (Fig. 1(d)). Common sensor suites for UGVs in agriculture include 2D and 3D LiDAR, as well as stereo, time-of-flight, and monocular cameras as exteroceptive sensors to acquire data from the surrounding environment. Furthermore, Real-Time Kinematics positioning systems (RTK-GNSS), often coupled with Inertial Measurement Units (IMUs) are adopted for localization purposes.

A recent example is given by the remotely-controlled compact platform for in-row under-canopy crop monitoring developed in [17] (Fig. 1(e)). The novelty



(a) Vinescout [11]. (b) ByeLab [24]. (c) Tracked robot [30].

(d) Bonirob [6]. (e) Undercanopy UGV [17]. (f) Summit [8].

Fig. 1. Examples of robotic systems for mapping in agriculture.

of that system is the capability of capturing images on both sides of the UGV, by means of one front camera equipped with fisheye lens only.

Another interesting UGV is Bonirob [6] (Fig. 1(d)), which features a complete sensor suite, including a multi-spectral camera. It is used to collect an open-source large-scale agricultural data set. Nevertheless, only a paucity of robotic systems manage to superimpose radiometric information to the point cloud acquired with laser scanners. Byelab [29] (Fig. 1(b)), and the robot developed by Clamens et al. [8] (Fig. 1(f)) are among them.

AgRob V16 [25] is developed for vineyards monitoring and supports two interchangeable sensor suites: the former includes a monocular camera with special light filters to extract NDVI images; the latter configuration comprises a 3D LiDAR, a robotic arm manipulator, and a thermal camera. However, thermal data are not merged with the point cloud acquired by the LiDAR. To the best of our knowledge, no autonomous robotic system are able to directly superimpose thermal information to an agricultural 3D map.

BrambleBee [31] is similar to AgRobV16, and it is capable of pollinating with its end-effector: an endoscope camera is used for additional guidance of the robotic arm. Sensors carried by a robotic arm provide a flexible solution to the occlusion problem that is common in image-based phenotyping [4], as they manage to position and orient cameras at the best viewpoint. No LiDAR and multi-spectral cameras are found in literature in a eye-in-hand configuration yet. Most UGVs rely on storage memories to manage data, requiring a frequent operator support. Internet of Robotic Things will be a solution to this problem. Moreover, storing data on clouds will make them easily available from remote.

Complete sensor suites ensure for a flexible system, but increase the energy consumption. To solve this problem, multiple and modular sensor suites could be developed. Moreover, for large-scale operations renewable and sustainable energy sources, like solar panels and hydrogen fuel cells should be integrated. Swarm robotics could be another solution to extend the range of action, since the farmland can be divided into sub-maps covered by different robots. Finally, attention should be given to the durability and availability of these systems and sensors as they operate in harsh outside environments.

3 Localization and mapping

In this section, an overview on recent localization and mapping strategies that overcome pose estimation issues in rough agricultural terrains is given. Classic localization methods (based on wheel encoders, IMUs and GNSS data) do not often provide adequate accuracy and SLAM algorithms are therefore needed. SLAM problem refers to the estimation of the state of the robot concurrently with the construction of a model of the environment. With this method, data deriving from the previously mentioned sensors are integrated with LiDAR (known as LiDAR SLAM) or cameras (i.e., Visual SLAM).

The strategy of Visual SLAM is to sequentially estimate the camera poses by tracking feature points in the image sequence. In this context, it is worth citing RTAB-Map [15], an open-source software that provides feature-based Visual SLAM with loop closure (i.e., the recognition of a previously mapped region, with the aim of reducing trajectory drift and increasing map accuracy). RTAB-Map is frequently used in the agricultural research field [23,19,20]; nevertheless, conflicting results regarding its performance are found in literature and additional tests in agricultural environments are needed. In [22], RTAB-Map is improved aligning LiDAR scans with a 2D map and integrating wheel odometry.

The main solution for LiDAR SLAM is the scan-matching approach, usually based on the Iterative Closest Point (ICP) algorithm for the alignment of pairs of point clouds, followed by graph optimization [30]. To obtain higher accuracy and lower computational requirements, in [3] an online clustering algorithm is integrated with the previous VineSLAM method [25] to reduce data size and speed up the refinement step based on ICP.

Fusing Visual and 3D LiDAR SLAM is a promising approach, but it is not fully implemented in agricultural UGVs yet. To this regard, a benchmark of the up-to-date SLAM algorithms in agricultural field is needed, together with a standard for the ground truth. Besides, the environment dictates the conditions on which sensor is the most advantageous, and, therefore, the robot should be able to choose the best data source according to the external conditions.

The application of LiDAR and RGB cameras is a common practice and many algorithms are available (also open-source) that use data acquired by these sensors for navigation and mapping. On the contrary, multi-spectral and hyper-spectral cameras, fundamental in agriculture, are not extensively considered in the field of computer vision and robotics, and there is a lack of methods to adequately merge the data acquired with these sensors with most common ones.

4 Path planning

Planning the path of a robot consists of finding a sequence of translations and rotations from a starting point to a goal one, while avoiding obstacles in the environment [26]. Coverage path planning is the task of determining a path that passes through all points of an area, and it is advanced in this field, given its need for operations such as harvesting, pruning and spraying. A common solution is to use cell decomposition, or graph Voronoi diagram [31], and row following (exploiting particle filters or Kalman filters [5]), with zig-zag patterns.

Regarding point-to-point path planning in static environment, several algorithms have been tested: artificial potential field, sampling based methods, genetic algorithms, and methods that fall into the Traveling Salesman Problem. In [16], for example, the Ant Colony algorithm, based on the behavior of ants searching for food, is used to reduce total measurement time, improve efficiency and save energy of an UGV operating in a potato field. Further discrete optimization algorithms (e.g., A* [25], Dijkstra, RRT* [7]) have been modified to rely on robot pose and kinematic constraints or to provide planning for automatic recharging system and a solution to avoid repetitive paths, minimizing the soil compaction effects. In [7], RRT* is used in combination with the Reeds-Shepp algorithm, considering non-holonomic constraints of the robot, to deal with narrow pathways of a greenhouse.

There is a lack of online solutions for path planning in dynamic environments. A popular tool is ROS Navigation Stack [31]: using Dijkstra for high level path planning and the dynamic window approach for obstacle avoidance. However, further tests are needed to provide a guideline on the best parameters for this navigation framework in each agricultural environment.

All the above methods require prior information: manual measures [31], satellite images [25], or 2D and 3D maps. To acquire these information, collaboration with unmanned aerial vehicle would be useful, as a substitute to the above sources to provide an updated view of the current conditions. Moreover, up-to-date exploration algorithms not relying on prior data should be exploited [28].

5 Application of artificial intelligence

Technologies from areas including data science and AI can be used alongside autonomous systems to automatically fuse and interpret collected data. Nowadays, classification and segmentation algorithms are increasingly applied to add semantic information to the map. In [23], a supervised learning method is proposed to perform terrain characterization, using color and geometric feature and measuring wheel slip, rolling resistance and vibration response experienced by the vehicle. Among the various alternatives provided by convolutional neural networks (CNNs), two can be highlighted: object detection models and image segmentation models. The former can build a bounding box corresponding to each investigated class in the image, whereas the latter create a pixel-wise mask for each object. With the pixel-wise segmentation technique it is possible to obtain a far more granular understanding of objects, with respect to the bounding boxes technique, with the disadvantage that annotating each class requires a greater effort. In [10], You Only Look Once (YOLO), the preeminent solution for object detection in PA, is used to build a hybrid topological map with semantic classification and key location estimation. Instead, segmentation is used in [20] to obtain a 3D map with semantic labels: this probabilistic information is used by the UGV to recognize leaves as traversable regions inside a greenhouse.

In real-world scenarios, data collection for the network training can be challenging and time-expensive. Moreover, the system must be robust to the variability of the field to avoid re-training. To overcome this problem, Generative Adversarial Networks (GANs) can be used to generate photorealistic agricultural images, based on semantic information [32]. The learning process can also be performed by transferring knowledge from a given task that is already learned, and the training can involve only a subset of layers of the CNN. This method, called transfer learning, is used in [25] to detect vine trunks and to develop a feature-based localization framework to navigate in the vineyard. YOLO afterward is used in [19] to perform person detection and following.

Future work will address the use of bounding boxes to improve the quality of point clouds and to remove workers and agricultural machines from it. Deep learning algorithms for timely classification and recognition of diseases are also required to increase the crop quality and yield. This could be achieved by preparing plant pathology data sets with diseases in the early stages. AI can also improve exteroceptive capabilities of the system. For example, Shu et al. [27] presented, to the best of our knowledge, the first evaluation results for monocular SLAM. Their work explores unsupervised depth estimation in a soy-bean field, by simulating RGB-D SLAM. Not relying on LiDAR, this method is less expensive and power consuming. Finally, as UGVs can accumulate a large quantity of data, cloud computing will enhance the data processing efficacy, offer higher data security and scalability, and minimize costs.

6 Conclusion

In this article, trends and future developments in mobile robotics for 3D mapping in agriculture have been surveyed. Recent examples of UGVs have been reported emphasizing the importance of developing platforms capable of moving in rough terrains, and sensors to provide information about volume, height and health of plants, among others. Then, SLAM approaches and path planning algorithms have been discussed, pointing out that more effort will be necessary to deal with unknown and dynamic harsh environment, during mapping and phenotyping tasks. Finally, insights into applications of AI to robotic mapping have been given to evaluate the potentiality of neural networks. The three topics covered in this paper must be integrated in a tightly coupled manner in the robotic system, to make it autonomous for mapping, and to compensate for the weaknesses of the standalone solutions. In the coming years there will be great progress in autonomous systems for PA thanks to multidisciplinary activities involving agronomy, robotics, and AI. Future works will address the creation of a taxonomy of hardware solutions and software capabilities of robotics systems in PA.

References

1. Adán, A., Quintana, B., Prieto, S.A.: Autonomous mobile scanning systems for the digitization of buildings: A review. Remote Sensing **11**(3), 306 (2019)
2. Aguiar, A.S., dos Santos, F.N., Cunha, J.B., Sobreira, H., Sousa, A.J.: Localization and mapping for robots in agriculture and forestry: A survey. Rob. **9**(4), 97 (2020)
3. Aguiar, A.S., dos Santos, F.N., Sobreira, H., Cunha, J.B., Sousa, A.J.: Particle filter refinement based on clustering procedures for high-dimensional localization and mapping systems. Robotics and Autonomous Systems **137**, 103725 (2021)
4. Atefi, A., Ge, Y., Pitla, S., Schnable, J.: Robotic technologies for high-throughput plant phenotyping: Contemporary reviews and future perspectives. Front. in Plant Science **12** (2021)
5. Blok, P.M., van Boheemen, K., van Evert, F.K., IJsselmuiden, J., Kim, G.H.: Robot navigation in orchards with localization based on particle filter and kalman filter. Computers and Electronics in Agriculture **157**, 261–269 (2019)
6. Chebrolu, N., Lottes, P., Schaefer, A., Winterhalter, W., Burgard, W., Stachniss, C.: Agricultural robot dataset for plant classification, localization and mapping on sugar beet fields. Int. J. of Rob. Research **36**(10), 1045–1052 (2017)
7. Choudhary, A., Kobayashi, Y., Arjonilla, F.J., Nagasaka, S., Koike, M.: Evaluation of mapping and path planning for non-holonomic mobile robot navigation in narrow pathway for agricultural application. In: Int. Symp. on System Int. pp. 17–22 (2021)
8. Clamens, T., Alexakis, G., Duverne, R., Seulin, R., Fauvet, E., Fofi, D.: Real-time multispectral image processing and registration on 3d point cloud for vineyard analysis. In: Int. Conf. on Computer Vision Theory and Applications (2021)
9. Duckett, T., Pearson, S., Blackmore, S., Grieve, B., Chen, W.H., Cielniak, G., Cleaversmith, J., Dai, J., Davis, S., Fox, C., et al.: Agricultural robotics: the future of robotic agriculture. UK-RAS White papers (2018)
10. Emmi, L., Le Flécher, E., Cadenat, V., Devy, M.: A hybrid representation of the environment to improve autonomous navigation of mobile robots in agriculture. Precision Agriculture **22**(2), 524–549 (2021)
11. Fernández-Novales, J., Saiz-Rubio, V., Barrio, I., Rovira-Más, F., Cuenca-Cuenca, A., Santos Alves, F., Valente, J., Tardaguila, J., Diago, M.P.: Monitoring and mapping vineyard water status using non-invasive technologies by a ground robot. Remote Sensing **13**(14), 2830 (2021)
12. Fountas, S., Mylonas, N., Malounas, I., Rodias, E., Hellmann Santos, C., Pekkeriet, E.: Agricultural robotics for field operations. Sensors **20**(9), 2672 (2020)
13. Kim, P., Park, J., Cho, Y.K., Kang, J.: Uav-assisted autonomous mobile robot navigation for as-is 3d data collection and registration in cluttered environments. Automation in Construction **106**, 102918 (2019)
14. Kurazume, R., Oshima, S., Nagakura, S., Jeong, Y., Iwashita, Y.: Automatic large-scale three dimensional modeling using cooperative multiple robots. Computer Vision and Image Understanding **157**, 25–42 (2017)

15. Labbé, M., Michaud, F.: Rtab-map as an open-source lidar and visual simultaneous localization and mapping library for large-scale and long-term online operation. Journal of Field Robotics **36**(2), 416–446 (2019)
16. Mai, T., Shao, S., Yun, Z.: The path planning of agricultural agv in potato ridge cultivation. Annals of Advanced Agricultural Sciences **3**(2) (2019)
17. Manish, R., Lin, Y.C., Ravi, R., Hasheminasab, S.M., Zhou, T., Habib, A.: Development of a miniaturized mobile mapping system for in-row, under-canopy phenotyping. Remote Sensing **13**(2), 276 (2021)
18. Maset, E., Scalera, L., Beinat, A., Cazorzi, F., Crosilla, F., Fusiello, A., Gasparetto, A.: Preliminary comparison between handheld and mobile robotic mapping systems. In: Int. Work. IFToMM for Sust. Dev. Goals. pp. 290–298. Springer (2021)
19. Masuzawa, H., Miura, J., Oishi, S.: Development of a mobile robot for harvest support in greenhouse horticulture—person following and mapping. In: Int. Symp. on Sys. Int. pp. 541–546. IEEE (2017)
20. Matsuzaki, S., Masuzawa, H., Miura, J., Oishi, S.: 3d semantic mapping in greenhouses for agricultural mobile robots with robust object recognition using robots' trajectory. In: IEEE Int. Conf. on Systems, Man, and Cyb. pp. 357–362 (2018)
21. Oliveira, L.F., Moreira, A.P., Silva, M.F.: Advances in agriculture robotics: A state-of-the-art review and challenges ahead. Robotics **10**(2), 52 (2021)
22. Post, M.A., Bianco, A., Yan, X.T.: Autonomous navigation with ros for a mobile robot in agricultural fields. In: Int. Conf. on Inf. in Contr., Autom. and Rob. (2017)
23. Reina, G., Milella, A., Galati, R.: Terrain assessment for precision agriculture using vehicle dynamic modelling. Biosystems engineering **162**, 124–139 (2017)
24. Ristorto, G., Gallo, R., Gasparetto, A., Scalera, L., Vidoni, R., Mazzetto, F.: A mobile laboratory for orchard health status monitoring in precision farming. Chemical Eng. Trans. **58**, 661–666 (2017)
25. Santos, L., Santos, F., Mendes, J., Costa, P., Lima, J., Reis, R., Shinde, P.: Path planning aware of robot's center of mass for steep slope vineyards. Robotica **38**(4), 684–698 (2020)
26. Santos, L.C., Santos, F.N., Pires, E.S., Valente, A., Costa, P., Magalhães, S.: Path planning for ground robots in agriculture: A short review. In: Int. Conf. on Aut. Rob. Syst. and Comp. pp. 61–66. IEEE (2020)
27. Shu, F., Lesur, P., Xie, Y., Pagani, A., Stricker, D.: Slam in the field: An evaluation of monocular mapping and localization on challenging dynamic agricultural environment. In: Wint. Conf. on App. of Comp. Vis. pp. 1761–1771 (2021)
28. Umari, H., Mukhopadhyay, S.: Autonomous robotic exploration based on multiple rapidly-exploring randomized trees. In: IEEE/RSJ Int. Conf. on Int. Rob. and Syst. pp. 1396–1402 (2017)
29. Vidoni, R., Gallo, R., Ristorto, G., Carabin, G., Mazzetto, F., Scalera, L., Gasparetto, A.: Byelab: An agricultural mobile robot prototype for proximal sensing and precision farming. In: Int. Mech. Eng. Congr. and Exp. ASME (2017)
30. Wang, K., Zhou, J., Zhang, W., Zhang, B.: Mobile lidar scanning system combined with canopy morphology extracting methods for tree crown parameters evaluation in orchards. Sensors **21**(2), 339 (2021)
31. Yang, C., Watson, R.M., Gross, J.N., Gu, Y.: Localization algorithm design and evaluation for an autonomous pollination robot. In: Int. Tech. Meet. of the Sat. Div. of the Inst. of Nav. pp. 2702–2710 (2019)
32. Yang, Y., Zhang, J., Wu, K., Zhang, X., Sun, J., Peng, S., Li, J., Wang, M.: 3d point cloud on semantic information for wheat reconstruction. Agriculture **11**(5), 450 (2021)