robotics

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Editorial

Robotics and AI for Precision Agriculture

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To meet the rising food demand of a world population predicted to reach 9.8 billion in 2050, while also guaranteeing environmental sustainability, it is critical to improve crop production by introducing new technologies and artificial intelligence to accelerate the current transition towards the Agriculture 4.0 paradigm. In this context, precision agriculture aims to develop strategies based on observing, measuring, and responding to temporal and spatial variability to improve agricultural production sustainability. Unlike conventional methods of managing whole fields on the basis of theoretical average conditions that are rarely true throughout the entire area, precision agriculture recognizes the unique differences within the field. This strategy consists of adjusting management practices to take into account these specific differences at each site, thus optimizing resource utilization. Impressive progress has been achieved in the integration of artificial intelligence and robotics to develop precision agriculture systems, with many applications having been demonstrated, including automated fruit harvesting, pruning, crop phenotyping and monitoring, weed control, selective spraying of pesticides and fertilizers, and more. However, new challenges must be addressed in many areas of robotics, such as motion planning and control, manipulation, learning, perception, and locomotion, to further improve the capabilities and autonomy of farmer robots in challenging agricultural settings in both open field and greenhouse conditions. An underlying theme in agricultural robotics is the interdisciplinary nature that covers both robotics and natural sciences.

This Special Issue presents new innovative approaches in robotics for precision agriculture and artificial intelligence. Original contributions from researchers and practitioners on ideas and approaches to enable robotic systems in agriculture are reported. Attention is paid to fostering the connection between robotics and plant sciences to solve real-world problems. For example, in [1], an experimentally tested approach is described using semi-supervised learning to generate new data sets for semantic segmentation of vine trunks with very little human-annotated data, resulting in significant savings in time and resources. The creation of such datasets is a crucial step towards the development of autonomous robots for vineyard maintenance. Tree trunk detection is also the objective of the research presented in [2] that specializes in forestry environments. The paper contribution is three-fold: an open dataset of 5325 annotated forest images; a tree trunk detection Edge AI benchmark between 13 deep learning models evaluated on four edge devices (CPU, TPU, GPU and VPU); and a tree trunk mapping experiment using an OAK-D as a sensing device. Remaining in the context of precision forestry, a survey of the current state of the art in artificial perception and sensing for robots is presented in [3]. Based on this analysis, a roadmap is put forward to address the outstanding challenges in the corresponding scientific and technological landscape, namely the lack of training data for perception models, open software frameworks, robust solutions for multi-robot teams, end-user involvement, use case scenarios, computational resource planning, management solutions to satisfy real-time operation constraints, and systematic field testing.

Accurate mapping, localization, and obstacle detection are important for efficient and safe autonomous navigation of farmer robots. A guiding manager for autonomous mobile robots specialized in laser-based weeding tools is presented in [4]. The focus is on robot tracking, which combines a lateral controller, a spiral controller, and a linear speed controller

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to adjust to the different types of trajectories that are commonly followed in agricultural environments, such as straight lines and curves. The controllers have demonstrated their usefulness in different real work environments at different nominal speeds, validated on a tracked mobile platform, in complex and varying field conditions, including loose soil, stones, and humidity. In [5], a learning-by-demonstration framework based on Dynamic Movement Primitives (DMPs) is proposed, which could be effectively adopted to plan complex activities in agricultural robotics avoiding orientation discontinuity during motion learning. The proposed approach is tested on the Tiago robot during the fulfillment of four agricultural activities, such as digging, seeding, irrigation and harvesting. A nonlinear model predictive controller is presented in [6] to generate optimal trajectories for an omnidirectional robot. The results are provided on different trajectories and with moving obstacles along with considerations on controller performance.In the field of precision agriculture, the automation of sampling and harvesting operations plays a central role in expanding the possible application scenarios. Within this context, the design and prototyping of a novel underactuated tool for the harvesting of grapevines is described in [7]. As a use case, the proposed tool is customized for the gripper of the robotic arm mounted on the rover Agri.Q, a service robot conceived for agriculture automation. Robotic manipulation in cluttered environments is one of the challenges roboticists are currently facing. When the objects to handle are delicate fresh fruits, grasping is even more challenging. Detecting and localizing fruits with the accuracy necessary to grasp them is very difficult because of the large variability in the aspect and dimensions of each item. In [8], a solution that takes advantage of a state-of-the-art neural network and a novel enhanced 6D pose estimation method that integrates the depth map with the output of the neural network is proposed. Even with an accurate localization, grasping fruits with a suitable force to avoid slippage and damage is another challenge. This issue is addressed by resorting to a grasp controller based on tactile sensing. Experiments with real fresh fruits demonstrate that the overall proposed approach allows a robot to successfully grasp apples in various situations. In [9], a cable-driven parallel robot developed to automate repetitive and essential tasks in crop production in greenhouse and urban garden environments is introduced. Unlike conventional suspended cable robots, this robot incorporates four moving pulley systems in the frame, which significantly increases its workspace. The robot has been validated through simulations, where possible trajectories that the robot could follow depending on the tasks to be performed in the crop are presented. Stair climbing is one of the most challenging tasks for vehicles, especially when transporting people and heavy loads. Although many solutions have been proposed and demonstrated in practice, it is necessary to further improve their climbing ability and safety. In [10], a systematic review of the scientific and engineering literature on stair climbing is presented, providing brief descriptions of the mechanism and method of operation and highlighting the advantages and disadvantages of different types of climbing platform.

In many cases, multiple cooperating robots can be deployed to reduce task duration, perform an operation not possible with a single robot, or perform an operation more effectively. In [11], a cooperation strategy is demonstrated that allows two heterogeneous robots to collaborate to harvest grapes, and its implementation is demonstrated. More specifically, the cooperative grape harvesting task involves two heterogeneous robots, where one robot (i.e., the expert) is assigned the grape harvesting task, whereas the second robot (i.e., the helper) is tasked with supporting the harvesting task by carrying the harvested grapes. Field experiments have been conducted to first validate the effectiveness of the coordinated navigation algorithm and, second, to demonstrate the proposed cooperative harvesting method. In the same context, the research proposed in [12] aims to include mobile robots as complements to tractor in an agricultural context. The main idea is not to replace the human farmer, but to augment their capabilities by deploying mobile robots as assistants in field operations. The scheme is based on a leader–follower approach. The manned tractor is used as a leader, which will be taken as a reference point for a follower. The follower then takes the position of the leader as a target, and follows it in an autonomous manner.

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