agriculture

Editorial

Robots and Autonomous Machines for Sustainable Agriculture Production

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The global agriculture faces critical pressures, including an aging population, rising production costs, and labor shortages. As an important alternative solution for those challenges, robots and autonomous machines represent a high-level application of smart agriculture, which is based on a precise and resource-efficient approach that attempts to sustainably achieve a higher efficiency in the agricultural production with an increased quality. On the one hand, robotics and autonomous machines continue to expand in various new agricultural scenarios, while on the other hand, technologies such as deep learning and machine learning are increasingly used in agriculture, and their application in various scenarios of agricultural production has become more in-depth. By exploring the diverse methodologies employed in addressing such challenges, this Special Issue aims to advance the field and improve the efficiency of agricultural production through robotic and autonomous innovations.

In order to investigate the advancements in robots and autonomous systems for agriculture, using modeling, detection, and control technologies, emphasizing their potential in precision farming, crop protection, crop harvesting, etc., we have organized this Special Issue "Robots and Autonomous Machines for Agriculture Production (RAMAP)". The Special Issue of RAMAP has a total of 26 papers [1–26], and papers were submitted from eight countries: Spain, Italy, Germany, Brazil, China, Sweden, Czech Republic and Croatia. Moreover, the Special Issue covers a wide range of agricultural operations, including cotton planters [15], maize planters [2], apple harvesting [3,7,11], shrimp peeling [4], rice phenotyping [6], pests control [9], bales collection [8], pineapple processing [10], garlic seeding [12], agricultural film collecting [13], lettuce growth modelling [14], egg microcrack detection [17], forage pushing [18], fungus harvesting [24] and jujube pruning [25]. In terms of the research field, the Special Issue not only focused on robotic and its related application research, such as soft gripper design [3], autonomous robot [5], humanoid field-phenotyping robot [6], apples detection [7], manipulator motion planning [11], dairy robot [18], vineyard spraying robot [20], fungus harvesting robot [24] and orchard visual navigation [26], but also refers to intelligent agricultural machines in different scenarios on seeding [1,2,12,15], shrimp peeling [4], recycling film collecting [13], crop and monitoring [14], and agricultural products [16,17,23].

Agricultural robots are multi-degrees-of-freedom autonomous operation machines used in agricultural production, with perception, decision-making, control and execution capabilities, mainly including information perception systems, decision-making systems, operation actuators, that is sensing, decision making and execution. Overall, most of the papers in the Special Issue of RAMAP were grouped into four categories: sensing for the crop or machine system [1,4,7,9,10,12,16,17,22,23,26], methodological studies for decision-making and control [2,8,11,14,18,20,24], designs related to intelligent machinery execution [1,3,13,15,25] and systematic solutions [5,6,19,21].

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Generally, agricultural robots first need to sense the operating environment, the operating object and the state of the robot itself, and to provide the panoramic data related to the operating process to the agricultural robots to complete the operating tasks.

The first category has eleven papers under the following sub-heading: Intelligent sensing for the crop or machine system [1,4,7,9,10,12,16,17,22,23,26]. Currently, a large number of studies focus on deep learning techniques, which have shown their superb impact on robotic sensing applications, as reflected in this issue. Some papers utilized improved YOLO-based [7,23,26], CNN-based [12,16] or RCNN-based [9] methods to developed a detection model for operating target recognition or performance evaluation from the RGB images. To achieve more accuracy, faster and compacter models may be popular due to the cost-effective and feasiblity with low-computing platforms. The paper by Liu et al. [10] proposed a 3D localization algorithm to fuse the depth information based on multiangle image matching and YOLOv5 detection information. Some papers utilized the manual features combined with machine learning, such as the adaptive recognition boundary model [4], density-based lightning connection clustering [22], random forest [17], etc., to achieve target detection, due to a small training dataset or more efficient features.

For intelligent agricultural machines, Bai et al. [1] designed a monitoring system for the sowing quality of cotton precision planters, to realize the real-time monitoring of the cotton precision seeding operation processes and improve the intelligence level of cotton precision planters.

Generally, intelligent decision-making and intelligent control systems aim at deep fusion of perception information, cognitive reasoning, predictive planning, and coordinated control of agricultural robot perception and execution subsystem operations, which is the core element of agricultural robots.

The second category has seven papers under the following sub-heading: Methodological studies for decision making and control [2,8,11,14,18,20,24]. Three studies focus on the optimization of motion planning for robots. The paper by Latif et al. [8] optimized path planning approaches using a new autonomous articulated concept vehicle with neighborhood reach capabilities (AVN). The paper by Liu et al. [11] proposed a time-optimal rapidly exploring random tree (TO-RRT) algorithm to reduce the obstacle avoidance effect and increase picking efficiency of the manipulator. The paper by Yang et al. [24] proposes a multi-objective optimization algorithm of the multi-arm cooperative harvesting trajectory to improve the harvesting efficiency.

A novel method [14] for predicting the dynamic growth of leafy vegetables based on the in situ sensing of phenotypic and environmental data of batches is proposed to predict the dynamic fresh weight of substrate-cultivated lettuce grown in a solar greenhouse under normal water and fertilizer conditions. A model predictive control (MPC)-based approach [20] for vineyard spraying was presented to adapt to different vine row structures and suitable for real-time applications. Additionally, a control system [2] for an electrically driven precision maize seeder based on the CANopen protocol was designed. An obstacle avoidance strategy [18] based on the improved artificial potential field method is proposed for an autonomous navigation pusher robot.

The third category has seven papers under the following sub-heading: Designs related to intelligent machinery execution [3,13,15,25]. Zhang et al. [25] designed a pruning manipulator with five degrees of freedom for jujube trees. It is of reference value to solve the problems of poor working conditions and the labor intensity of manually pruning jujube trees. Chen et al. [3] developed a fin ray structure-based soft gripper mechanical model and its real-time servo-driven control strategy to reduce the potential danger of damage to the apple pericarps during robotic harvesting. Yu et al. [15] designed a cotton seeder duckbill welding robot to improve the automation, welding efficiency, and welding quality of duckbill welding of cotton seeds.

The final category has four papers under the following sub-heading: Systematic solutions [5,6,19,21]. Emmi et al. [5] presented an architecture to integrate the different components of an autonomous robot that provides access to the cloud, taking advantage of the services provided regarding data storage, scalability, accessibility, data sharing, and data analytics. Huang et al. [6] presents a new in-field interactive cognition phenotyping paradigm, and a humanoid robot equipped with image-acquiring sensory devices is designed containing an intuitive remote control for field phenotyping manipulations; subsequently, an attentional residual network (AtResNet) is proposed for rice tiller number recognition. The paper by Vasconcelos et al. [19] proposed a demo of agricultural field image data acquisition with a low-cost autonomous robot.

Precision agriculture, which addresses the spatial and temporal variability of soils and crops to reduce agricultural inputs and improve agricultural production reporting, varies greatly in implementation from country to country. Vrchota et al. [21] evaluated precision agriculture technologies' practical use in agricultural enterprises in the Czech Republic, which is a reference for the development and implementation of precision agriculture technology and equipment in each country.

In summary, this Special Issue highlights different approaches in the development of agricultural robots and intelligent agricultural machines in several agricultural application scenarios for scene and object perception, intelligent decision support methods, and operational mechanisms and their control. It is expected that the insights derived from this Special Issue will be useful to researchers related to the field of agricultural robots and autonomous machines.

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