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Editorial

Precision Operation Technology and Intelligent Equipment in Farmland

Jun Ni [1,2]

[1] College of Agriculture, Nanjing Agricultural University, Nanjing 210095, China; nijun@njau.edu.cn; Tel.: +86-25-8439-6593

[2] Collaborative Innovation Center for Modern Crop Production Co-Sponsored by Province and Ministry, Nanjing 210095, China

1. Introduction

Precision operation technology and intelligent equipment in farmland is centered on farmland cultivation, planting, management, harvesting, and other operations [1–4], integration of the Internet of Things [5–7], agricultural modeling [5,8–13], and robotics [11,14–17], and other advanced technologies. In doing so, an intelligent farm equipment system, with functions such as information collection [8,12,13,16], prescription generation [6,17–19], intelligent control [20,21], and variable implementation, can be built [11]. This system is highly integrated with agricultural machinery–agronomy–information aspects. It can fully reflect the concept of crop production in accordance with in situ conditions, intelligent management, maximizing productivity in farming, and environment protection. The theme of this Special Issue is cutting-edge research on precision farming and intelligent equipment; twelve research papers and one review article have been published, which are related to the fields of agricultural sensors, machine–crop–soil interactions, crop production modeling, new agricultural machinery, and field robots.

2. Papers in this Special Issue

Consumers are increasingly paying attention to the quality and safety of grains, which are a necessity for human life [22–26]. The review articles [27] discussed the application and prospect of different sensing mechanisms, such as acoustics and optics, and sensing equipment used in grain quality detection. Current methods and products that have been able to realize high-precision detection for different grain quality indicators have been summarized. Meanwhile, some difficulties in applications have also been analyzed. These difficulties include the high cost of detection associated with full-waveband instruments and the unstable results of grain quality detection based on acoustic and thermal characteristics. The authors believe that the future research of grain quality detection is to reduce the cost, improve reliability, and realize a fusion of multiple quality indicators.

Lychee branch occlusion and overlap in the natural state is one of the key problems hindering accurate picking by robots [28,29]. The second paper in this Special Issue [30] proposed a method of branch segmentation for lychee harvesting based on the improved DeepLabv3+ routine. It introduces an attention mechanism to improve the feature extraction ability of the model, thereby overcoming the problem arising from lychee branch segmentation by training the model with a constructed dataset that contains 488 images of lychee plants and fruits under different conditions. The results of that research promote the practical application of lychee-picking robots, and in the future attention should be paid to model lightweighting to increase the speed of model analysis.

Seedling cultivation and transplanting can improve the production and quality of vegetables [31–33]. To reduce the rate of root damage during automatic transplanting of cucumber seedlings, the third article of this Special Issue [34] discussed the effects of biochar, water content, and addition of nitrogen fertilizer on the cultivation of cucumber

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seedlings. The results showed that there were complex interactions among the variables related to crop growth, and that a preferred mixing ratio of substrate nutrients could improve water and nitrogen utilization in cucumber seedling cultivation. This article presents a catalyst for the development of automated transplanting cultivation operations.

Identifying occluded fruits in complex natural environments has always been a key topic for those with a research interest in image-processing techniques [35–40]. The authors of [41] used the improved YOLOv5 model for the detection of fruit targets. To reduce the leakage rate, a small target detection layer and a weighted frame fusion mechanism were added to the model. In doing so, the relationship between computational speed, accuracy, and computational volume were balanced to meet the actual needs imposed during practical fruit detection.

Pest detection is a prerequisite for precise drug application [42–44], and due to the small size, shape, color, and environmental similarity of some of the pest detection objects [45], the detection success rate is impaired, and the once high, stable crop yield is diminished [46–48]. The authors of [49] proposed a small-target detection algorithm to detect small-sized pests by taking the citrus woodlouse as an example, which improves the success rate of the model in detecting small targets by introducing an attention mechanism; the detection accuracy was 2.41% higher than that of the traditional model. This study provides a new method for the automatic detection of crop pests and diseases.

Reasonable control of the ratio of male to female flowers is key to elevating fruit quality and increasing yield [50,51], so the rapid counting of male and female flowers is key to modern farm management. The authors of [52] designed a fast and intelligent male and female flower detection system; the size of this developed detection model was only 5.91 MB, and the running power consumption was 10 W, which was significantly lower than that of the server and PC. The detection accuracy and speed met the requirements of male and female flower detection and statistical applications thereof. The authors can further pay attention to the integrity of the dataset in future research to improve the generalizability and stability of their innovative model.

The authors of [53] also conducted research on crop diseases and pests. Differing from the study published by the authors of [49], these authors considered five common pests and diseases as their research objectives, and proposed an improved, fully convolutional, first-level target detection network (FCOS-FL). This network adopted G-GhostNet-3.2 as the backbone network, realizing a lightweight model with an average accuracy of 91.3% for detection in the natural state, and the size of the model parameter set was reduced by 45%, which considerably accelerated its detection ability. Carried in a mobile terminal, it can quickly and accurately identify crop pests and diseases.

Currently, the measurement of soybean yields is mainly realized by detecting the number of pods in a single plant, and accurate counting remains a difficult problem due to the crowding and uneven distribution of pods [54,55]. Based on the VFNet detector, the authors of [56] proposed a deformable attention recurrent feature pyramid network, which was trained using a dense soybean dataset, with a final average accuracy of 90.35%. This is a significant improvement in accuracy compared to the previous detection model, and it has good stability for soybean yield measurement, with different numbers of single pods, plant shapes, and densities. In the future, it can be mounted on mobile terminals for field detection to minimize the workload in soybean breeding.

Nitrogen content is one of the important indicators for the detection of crop nutrients [57–59], which can directly affect crop photosynthesis and productivity [60–62]. Unmanned aerial vehicles (UAVs) have the characteristics of being mobile and flexible and less affected by the terrain [63,64]. The authors of [65] used a UAV platform to detect nitrogen in walnut trees, and proposed a canopy simulation method that contains spectral information of walnut tree canopies to realize canopy nitrogen inversion. The results of this study provide a theoretical basis and method of realization of the rapid detection of nutrient composition in large fruit trees.

Variable rate fertilization application is the key to improving fertilizer utilization efficiency in farmland: as the initial fertility of farmland is non-uniform, the use of uniform management methods is very likely to cause a decline in crop yield [66–68]. In previous research conducted by the authors of [69], the authors designed an automatic fertilizer application system to control the amount of fertilizer applied between different plots through electromagnetic flow meters. After comparison, the uniformity of fertilizer addition between plots treated with the designed fertilization system was significantly higher than that of manual fertilization by farmers. This system can accurately match the fertilization strategy, thereby improving rates of fertilizer utilization.

Peanut harvesting machinery is typically based on the soil, and the fruit density is different [70,71], so the choice of an appropriate fan speed and vibrating screen to complete the fruit cleaning is important; however, current studies seldom consider the adhesion characteristics between the soil peds, which leads to a poor clearing effect. The authors of [72] coupled discrete element and fluid simulation modules, conducted experimental research on different soil volumes and soil moisture contents, and optimized the appropriate suspension speed to improve the cleaning effect of peanut harvesting machinery.

Weed management is one of the most important tasks in the crop production management chain [73–75]. Due to the fact that some weeds are similar in appearance to the crop and are obscured by leaves of the crop itself, they are difficult to detect and recognize when using weed control equipment [76,77]. The authors of [78] proposed a weed detection model based on the improved Swin-Unet for common weeds in corn fields. This model can efficiently and accurately identify corn and weeds in complex corn fields and retain its effectiveness when it is used to identify weeds under occlusion conditions, with a single-frame processing time of 5.28×10^{-2} s. It can also dynamically detect weeds during the operation of weeding robots.

Pest protection for traditional fruit tree orchards is mainly achieved through manual spraying, and the unified management method is used for fruit trees with different growth conditions, which leads to low spraying efficiencies [79–81], sometimes leading to the poisoning of operators and nearby staff. The authors of [82] proposed a fruit tree canopy segmentation model against a complex orchard background to realize precise spraying of medicinal pesticidal solutions. This is convenient for calculating the canopy size and shape, and the image is captured using a RGB-D camera, which reduces interference arising from the image background during segmentation via depth information. This lightweight model can run directly in the embedded system, which provides a reference for the precise operation of the orchard-spraying robot.

3. Conclusions

The articles in this Special Issue cover new techniques, methods, and equipment for precision field operations. The current research into precision operating techniques and intelligent equipment in farmland mainly focuses on the use of information technology and intelligent control technology [83,84], and on the integration of agricultural production management models to design or improve agricultural machinery and equipment [85,86], resulting in results that contribute to the development of high-yield, high-quality, high-efficiency, ecologically sound, and safe modern agriculture, and the promotion of more intelligent agriculture. Suitable for precise cultivation, planting, management, harvesting, and other operations, "crop-soil-agricultural machinery" system interaction mechanisms and corrective model research, as well as interactions with the seeds, fertilizer, water, chemicals, precise control of the soil, crops, and weeds, and agricultural information-sensing methods and equipment breakthroughs [87,88], we can conclude that this will improve the productivity of fertilizers and chemicals, significantly increasing crop productivity, while reducing labor costs and protecting the farmland environment. However, some of these research results require further elucidation and analysis; future research should investigate the instability of detection models against complex backgrounds [52], the high cost of making the sensing equipment [27], etc.

Conflicts of Interest: The author declares no conflict of interest.

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