Introduction to the Special Issue on Precision Agricultural Robotics and Autonomous Farming Technologies

I. Introduction

GROWTH in world population, increasing urbanization and changing consumption habits mean demand for food production is predicted to increase dramatically over the coming decades. This increased demand for food production must be achieved despite challenges such as climate change, a limited supply of new arable land and difficulties in sourcing skilled farm labour.

Robotics and automation are likely to play a crucial role over the coming decades in meeting these challenges by helping to improve farm productivity. A vital component of these future autonomous agricultural systems is the development of robust and accurate perception systems for perceiving the agricultural environment.

Recently, the development of these agricultural perception systems in both research and industry has been spurred on by the emergence of new and increasingly cost-effective sensing modalities such as multi- and hyper-spectral imaging, high-resolution cameras, LiDAR, radar and centimetre precision GPS. These sensing modalities have been complemented by advances in the size and affordability of computing power and increasingly capable algorithms and the rise of deep learning.

Based on the content of this special issue, two set of technical challenges can be identified to be facing the broad adoption of agricultural robotics. The first set is related to the robotics systems themselves. This set of challenges are not unique to agricultural robotics but also faces any autonomous system that needs to operate in challenging environmental conditions. Some of these challenges addressed in this special issue are localization, obstacle avoidance and path planning.

The second set of challenges is related to the agricultural tasks themselves, such as weed-crop classification, fruit quality estimation, seed sorting, crop row detection, soil compactness mapping and vegetables and fruits manipulation after harvesting. The letters in this special issue addressed these type of challenges while working with a wide range of crops such as canola, corn, leek, medium and tiny sugarbeet, sugarcane billets, sweet peppers, and sunn hemp (seeds).

II. Guide to the Special Issue

In our special issue, **37** papers were submitted and **12** were published in IEEE Robotics and Automation Letters (with IROS 2018 conference option), volume 3, issue. 4 with **32%** acceptance rate. It is noticeable that 60% of papers addressed problems in perception using either computer vision or deep learning approaches. This fact sufficiently envisions the current momentum in machine learning (especially deep neural networks) and GPU computing techniques for agricultural robotics.

Unmanned ground vehicle (UGV) navigation using various light-weight sensors such as vision, IMU, and LiDAR was another popular research topic in the issue. Four papers (33%) were published on this topic.

Regarding manipulation and harvesting, we only had one paper published. This may be attributed to challenges in a real-world physical interaction that requires a complete robotic system; accurate perception module, sophisticated manipulator design, and its motion planning while maintaining high degree of dexterity, and efficient end-effector design. We expect to see more studies on this topic in near future.

In regarding crops considered in the letters of this special issue, nine crops appeared namely; canola, corn, leek, sugar beet, sugar cane billets, sweet peppers, seeds of sunn hemp, iceberg lettuce, and carrot. Three flowers of apple, peach and pear and trees of three crops, plum, walnut, and almond, in orchards were taken into consideration.

The editorial is organized as follows; we categorize 12 papers into four categories depending on their research topic; Data-driven deep learning approaches for agricultural robotics, traditional Computer vision in agricultural robotics, unmanned ground vehicle navigation in agricultural robotics followed by Harvesting robotics in Horticulture. Finally, we summarize publicly available datasets that were newly introduced in our special issue and we, the guest editors, believe these studies and datasets can benefit to agricultural robotics community and enable researchers to take advantages of a high-fidelity and high-quality dataset for their future work.

A. Data-Driven Deep Learning Approaches for Agricultural Robotics

In this issue, deep learning dominates as the approach for pattern recognition with applications ranging from seed purity detection to fruit ripeness estimation. The presented approaches build on successful deep convolutional neural networks architectures (e.g. Faster-RCNN and ResNet) and modify these networks to accept additional spatial, temporal and visual data unique to the task.

Halstead *et al.* address the problem of fruit quantity and ripeness estimation with the aim of assigning labor during the harvesting of sweet peppers. The ripeness of the fruit is jointly

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estimated in the same detection deep network by modifying a Faster-RCNN network and adding a parallel layer. The results show that the proposed method leads to better results than when learning ripeness as an extra class.

Lottes *et al.* utilise spatial information when using a fully convolutional neural network for the task of robust crop-weed classification. The aim is to reduce the use of broad-spectrum herbicides by enabling robots to perform targeted weed control. The primary challenge addressed in this work is the significant change in environmental appearance in the field over time (e.g. weed pressure, weed types, growth stages of the crop, visual appearance, and soil conditions).

Heo *et al.* engineered a 500-fps seed sorter system that uses low-latency detection and tracking based on a deep neural network. Such a system eliminates the tradeoff between speed and accuracy that affect seed sorting systems by utilising parallel CPU and GPU computations.

Dias *et al.* proposes the fine-tuning of an end-to-end residual convolutional neural network to automate the process of bloom intensity estimation (i.e. estimating the number of flowers present in an orchard). An image refinement stage is performed on the output of the flower segmentation by the deep network.

B. Traditional Computer Vision in Agricultural Robotics

Computer vision such as conventional image processing, feature extraction and matching, and has played a significant role in agricultural robotics for decades. Five letters in this Special Issue present novel computer vision solutions to tackle real-world problems in agricultural robotics.

Chebrolu *et al.* proposed a long-term image registration method tailored to agricultural fields by utilizing the geometry of crop (sugarbeet) arrangements. This enables to match crop images taken from a UAV across multiple spatiotemporal sessions over a crop's growth time-frame. Given the matches, a 3D model of the field is calculated with a temporal dimension capturing the evolution of the growing plants in the field. For a use case, the authors demonstrated monitoring crop growth parameters such as leaf area index over sessions using the proposed approach.

Computer vision technique is one of the popular approaches for crop quality evaluation. Alencastre-Miranda *et al.* addressed a vision-based sugar cane billets analysis; image acquisition, pre-processing, segmentation followed by feature extraction and classification. Bullets were classified into 6 classes depending on their level of damage and the results showed 90% successful in the classification of damaged billet.

Bosilj *et al.* demonstrated the impact of multiscale and content-driven morphology-based features (i.e., attribute profiles) for pixel-wise plant-type classification. Attribute profiles descriptors were taken into considerations for the crop and weed classification task and extensively evaluated on publicly available sugarbeet and carrot datasets by comparing HOG, and LBP descriptors that have been widely used in precision agriculture domain. In this letter, the authors showed promising segmentation results while maintaining computational complexity and providing descriptors at a higher resolution.

C. Unmanned Ground Vehicle (UGV) Navigation in Agricultural Robotics

UGV navigation is fundamental for autonomous operation within agriculture context. Robots should be able to localize themselves with respect to surroundings (e.g., orchard, greenhouse, or wide open fields) and be capable of analyzing the terrain in order to distinguish traversable and nontraversable area for the subsequent motion planning. We have four letters addressing these problems in the special issue as follows.

Winterhalter *et al.* proposed a robust crop row detection approach using the Hough transform. In the experiments, five crop (Canola, Corn, Leek, medium and tiny sugar beet) fields were considered and three Hough transform variants were proposed and evaluated.

Fentane *et al.* presented a method of creating spatial maps of soil condition with an outdoor mobile robot. Traditionally, data are collected manually then soil maps are constructed offline that is laborious and costly, limiting the quality and resolution of the resulting information. The proposed approach leverages Kringing to generate variance maps of a target environment from a given set of samples. The probabilistic maps are used as a reward function to plan paths reducing uncertainty for efficient data collection. Several exploration strategies (coverage, next-best-view, adaptive sampling) are compared using pre-recorded experimental data for the application of soil compaction mapping. Their performance is evaluated in terms of uncertainty/error reductions over time.

Marco Imperoli *et al.* presented a framework for fusing a large number of sensors in a pose graph optimization strategy. This approach is for the localization of ground-based agricultural vehicles, with a focus on freeing these systems from the need to use highly expensive GPS based solutions with base-stations. They present a robust and accurate three-dimensional (3-D) global pose estimation framework, designed to take full advantage of heterogeneous sensory data. They show that their approach provides accurate results even if the GPS unexpectedly changes positioning mode through the experiments.

The paper written by Durand-Petiteville *et al.* deals with autonomous farming and with the autonomous navigation of an agricultural robot in orchards, especially for typical semi-structured environments where the dense canopy prevents from using GPS signal, so detects and localize trees for localizing the vehicle. The key idea is to find the tree trunks by detecting their shadows, which are materialized by concavities in the obtained point cloud. They used four stereo cameras that provide a point cloud characterizing the environment. They tested their method in several different orchards, and compared the performance of the proposed method with other approaches from the literature.

D. Harvesting Robotics in Horticulture

In this special issue, we only had one letter in regards harvesting problem. This fact may be attributed from multiple factors such as the development of an automated harvesting system requires a tightly-coupled complete pipeline between perception and action, and it is difficult to achieve high success rate in unstructured and natural farm environments. Hughes *et al.* applied computer vision for detecting the outermost leaves of iceberg lettuces and peeling using a suction mechanism. A thresholding in LAB color space and conventional image processing applied with a prior shape knowledge to detect the center and stem of the lettuce. By horizontal pushing it, a lettuce can be oriented with the outermost leaf on top for the subsequent leaf removal and lifting using a vacuum suction cup. The center and stem were detected with 100% and 81% accuracy respectively.

III. Publicly Available Data Sets

In this section, we summarize datasets that are newly introduced/mentioned in the letters from the special issue. There are **five** new datasets including GPS, IMU, LiDAR, multispectral images, RGB images, soil compaction measurements taken from ground or aerial robots. Two crops (sugar cane billets, sugar beets) and flowers of three crops (apple, peach, and pear) appeared in the images. Securing high-fidelity and quality dataset is significantly important in agriculture domain and it also requires tremendous time, efforts, and resources (e.g., long turnaround for dataset collection due to weather and seasons dependency). Great contributions from authors who willing to share their datasets (41% of published papers) made the special issue possible to introduce them in this editorial;

1) JP Fentanes *et al.*, 3-D Soil Compaction Mapping Through Kriging-Based Exploration With a Mobile Robot
    a) URL: https://goo.gl/u2Tpdo
    b) Short data attribute description: soil compaction information for two fields, (last access on 3/Sep/2018).
2) N. Chebrolu *et al.*, Robust Long-Term Registration of UAV Images of Crop Fields for Precision Agriculture
    a) URL: https://goo.gl/vCxeip
    b) Short data attribute description: raw aerial images (Nadir view) of sugarbeet fields taken from commercial grade rolling shutter cameras, (last access on 3/Sep/2018).
3) M. Imperoli *et al.*, An Effective Multi-Cue Positioning System for Agricultural Robotics
    a) URL: https://goo.gl/enLLDL
    b) Short data attribute description: many sensors measurements from a UGV (odometry, multispectral images, IMU, GPS, LiDAR, RGB images (glocal shutter)), (last access on 3/Sep/2018).
4) M. Alencastre-Miranda *et al.*, Robotics for Sugarcane Cultivation: Analysis of Billet Quality using Computer Vision
    a) URL: https://goo.gl/u4Aa4u
    b) Short data attribute description: images of sugarcane billets categorized into 6 classes depending on their level of damage, (last access on 3/Sep/2018).
5) P. Ambrozio Dias *et al.*, Multi-species fruit flower detection using a refined semantic segmentation network
    a) URL: https://goo.gl/Jdvgv8
    b) Short data attribute description: four sets of flower images, from three different species: apple, peach, and pear. An annotated dataset with pixel-accurate labels (ground truth) for flower segmentation on high resolution images (last access on 3/Sep/2013).

These datasets were thoroughly prepared by the authors and peer-reviewed by RA-L reviewers. We, guest editors, hope that the datasets can benefit to agricultural robotics community and enable robotists to make use of them for future studies.

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Appendix
Related Work

1) N. Chebrolu, T. Lbe, and C. Stachniss, “Robust long-term registration of UAV images of crop fields for precision agriculture,” *IEEE Robot. Autom. Lett.*, vol. 3, no. 4, pp. 3097–3104, Oct. 2018, doi: 10.1109/LRA.2018.2849603.
2) M. A. Miranda, J. Davidson, R. M. Johnson, H. Waguespack, and I. Hermano Krebs, “Robotics for sugarcane cultivation: Analysis of billet quality using computer vision,” *IEEE Robot. Autom. Lett.*, vol. 3, no. 4, pp. 3828–3835, Oct. 2018, doi: 10.1109/LRA.2018.2856999.
3) M. Halstead, C. McCool, S. Denman, T. Perez, and C. Fookes, “Fruit quantity and ripeness estimation using a robotic vision system,” *IEEE Robot. Autom. Lett.*, vol. 3, no. 4, pp. 2995–3002, Oct. 2018, doi: 10.1109/LRA.2018.2849514.
4) P. Lottes, J. Behley, A. Milioto, and C. Stachniss, “Fully convolutional networks with sequential information for robust crop and weed detection in precision farming,” *IEEE Robot. Autom. Lett.*, vol. 3, no. 4, pp. 2870–2877, Oct. 2018, doi: 10.1109/LRA.2018.2846289.
5) M. Imperoli, C. Potena, D. Nardi, G. Grisetti, and A. Pretto, “An effective multi-cue positioning system for agricultural robotics,” *IEEE Robot. Autom. Lett.*, vol. 3, no. 4, pp. 3685–3692, Oct. 2018, doi: 10.1109/LRA.2018.2855052.

6) P. Bosilj, T. Duckett, and G. Cielniak, "Analysis of morphology-based features for classification of crop and weeds in precision agriculture," *IEEE Robot. Autom. Lett.*, vol. 3, no. 4, pp. 2950–2956, Oct. 2018, doi: 10.1109/LRA.2018.2848305.
7) Y. Heo, S. Kim, D. Kim, K. Lee, and W. Chung, "Super-high-purity seed sorter using low-latency image-recognition based on deep learning," *IEEE Robot. Autom. Lett.*, vol. 3, no. 4, pp. 3035–3042, Oct. 2018, doi: 10.1109/LRA.2018.2849513.
8) W. Winterhalter, F. Veronika Fleckenstein, C. Dornhege, and W. Burgard, "Crop row detection on tiny plants with the pattern hough transform," *IEEE Robot. Autom. Lett.*, vol. 3, no. 4, pp. 3394–3401, Oct. 2018, doi: 10.1109/LRA.2018.2852841.
9) J. Pulido Fentanes, L. Gould, T. Duckett, S. Pearson, and G. Cielniak, "3D soil compaction mapping through kriging-based exploration with a mobile robot," *IEEE Robot. Autom. Lett.*, vol. 3, no. 4, pp. 3066–3072, Oct. 2018, doi: 10.1109/LRA.2018.2849567.
10) J. Hughes, L. Scimeca, L. Ifrim, P. Maiolino, and F. Iida, "Achieving robotically peeled lettuce," *IEEE Robot. Autom. Lett.*, vol. 3, no. 4, pp. 4337–4342, Oct. 2018, doi: 10.1109/LRA.2018.2855043.
11) P. Ambrozio Dias, A. Tabb, and H. Medeiros, "Multi-species fruit flower detection using a refined semantic segmentation network," *IEEE Robot. Autom. Lett.*, vol. 3, no. 4, pp. 3003–3010, Oct. 2018, doi: 10.1109/LRA.2018.2849498.
12) E. Flecher, V. Cadenat, T. Sentenac, and S. Vougioukas, "Tree detection with low-cost 3D sensors for autonomous navigation in orchards," *IEEE Robot. Autom. Lett.*, vol. 3, no. 4, pp. 3876–3883, Oct. 2018, doi: 10.1109/LRA.2018.2857005.

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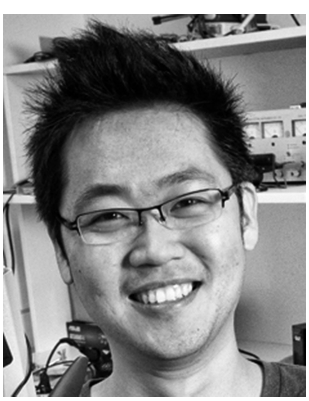

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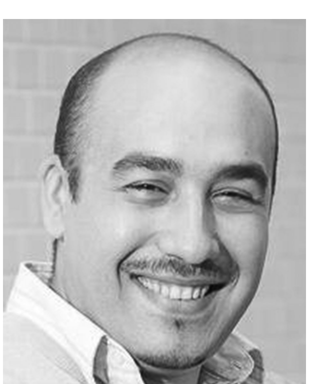

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