Research review on AI and Machine learning related works

Wei Zhao

Computer Sciences, University of Wisconsin–Madison, Madison

Department of Biological System Engineering, University of Wisconsin-Madison, Madison

Research Abstract

AI farming concepts have made significant contributions to increase food production and sustainability in the 21st century. These systems combine software and hardware that allows farmers to measure, monitor and control certain agronomic parameters. Smart farming technologies are becoming more prominent with technological advances in farming in fields of automation, ICT (information and communication technology), and robotics. Several applications of artificial intelligence (AI) are already developed for use in agriculture and farming purposes and it is anticipated that use of "AI farming" will assist the agriculture sector in the future to drive more efficient production.

To understand how to leverage the advantages of AI farming system in developing innovative farming applications, the following questions need to be answered: (1) What kinds of sensors should be used and data collected considering the cost and efficiency? (2) How do we seamlessly transfer new AI technologies from other industries to agricultural problems which have different requirements in terms of accuracy, scalability, operation, environment, etc. (3) What customized and innovative method should be developed dedicated to agriculture on the top of current general

AI technologies? and (4) How should we leverage the advantages of smart farming?

The automated mapping and navigation system could be a cornerstone of most autonomous agricultural system. Accordingly, we propose a ground-level mapping and navigating system based on computer vision technology (Mesh Simultaneous Localization and Mapping algorithm, Mesh-SLAM) and Internet of Things (IoT), to generate a 3D farm map on both the edge side and cloud. Our evaluation indicates that: 1) this Mesh-SLAM algorithm outperforms in mapping and localization precision, accuracy, and yield prediction error (resolution at centimeter); and 2) The scalability and flexibility of the IoT architecture make the system modularized, easy adding/removing new functional modules or IoT sensors. We conclude the trade-off between cost and performance widely augments the feasibility and practical implementation of this system in real farms.

Second, we present a sensing algorithm, a low-cost, robot-mounted, multidimensional map augmentation method that can track robot movements, monitor the surrounding environment, and link all the factors to the 3D map, thereby providing useful analytics to task planning, route planning and robot operators. The method leverages IMU sensors to gather mobility data for every individual robot. The ability to detect obstacles allows us to further augment the insight of the mapping method as a 4D or even higher dimension map rather easily. In this chapter, we attempted to provide analytics and data fusion from several specific aspects of the robot working environment. We believe that our farmland sensing approach has many more interesting and useful applications in similar agriculture environments.

Finally, we further develop computer vision-based crop detection with unmanned aerial vehicle (UAV) acquired images. This is a critical tool for precision agriculture, but object detection using deep learning algorithms rely on a significant amount of manually prelabeled training datasets as ground truths. Field object detection such as bales is especially difficult because of 1) long-period images acquisitions under different illumination conditions and seasons, 2) limited existing prelabeled data, and 3) few pretrained model and research as reference. Related work augments the bale detection accuracy only using limited data collection and labeling, by building an innovative algorithms pipeline. This approach has strong scalability on many other crops and field objects and will significantly enable precision agriculture techniques.

Combining all the created systems, we construct an agriculture AI system with multiple innovative algorithms. This large scope of system and pieces of algorithms fill in needed gaps for creating maps to enable smart agriculture, while also providing a valuable dataset and algorithms for future researchers.

AI Technology and Digital Workforce

Site-specific and chemical application: With the help of precision agriculture (site-specific applications), farmers can take advantage of localized data about the soil status, growing status, and other site-specific data to optimize the management of the farm. Evert et al. [1] showed in their study that crop spectral reflectance made be used as a vegetation index to determine crop health and amount. The development of site-specific variable-rate devices – precise spreaders, sprayers, on-board rate controllers, etc. – make the field work easier than before. Basso et al. [2] created a simulation approach that can conduct quantify studies on N-leaching and field yields under various environment, chemical usage and soil conditions. This method helps manage N-fertilizer-rate related to precipitation-based water availability and radiation. The other study by Basso et al. [3] also showed the advantage of SALUS-model on economics and environment when using site-specific fertilizer applications on segmented field with year as data collection unit.

Besides the studies around using N-fertilizer to enhance crop yield, recent studies have also considered the environmental impact related to N-fertilization, including nitrate leaching and nitrous oxide emissions. This precision agriculture technique can offer insights to management strategy on crops under various environments and soil conditions.

Image Acquisitions: To collect the images as inputs for the computer vision, using Unmanned Aerial Vehicle (UAV) is an efficient approach, which has been widely used in precision agriculture as well as many other fields, such as path planning, design, and livestock monitoring [4]. UAV combined with computer vision can also contribute to remote sensing to help inform farmers about the geo-specific crop yield and identify crop diseases [5]. Sometimes, decisions are required to be made off-board once the data have been collected and processed by the UAV, based on the information provided by the images processed from the computer vision technique [6]. For example, UAVs can be used to detect a potential issue, and then obtain high-resolution images or inspect and apply treatments correspondingly.

AI Technology Aided Autonomous System

An autonomous system is build based on precise maps created with path, terrain, crops, and other objects. Crop monitoring is also essential to allow robots to distinguish the crop from weeds, monitor plant health, and determine crop maturity. Computer vision implemented via low-cost visual sensors provides strong support for both local navigation and crop monitoring. However, there are certain related technical challenges in rural fields including data transmission with high bandwidth and high speed, system scalability in different sizes of land, mapping and localization accuracy, updating and maintenance, etc. Rapid advancements in computer vision, mapping, and the Internet of Things (IoT) have provided some solutions as follows.

A guidance system capable of being scalable to the spatial range of the agriculture applications, specifically large farmlands, is the key step to achieve high agricultural efficiency. A three-dimensional (3D) navigation system, which can guide a robot autonomously, is a necessary step to enable plant monitoring. Thus, mobile robotics should have precious information about their position and be connected with the other robotics via IoT architecture.

AI Technologies for Agriculture

Transfer Learning and Domain Adaptation. Transfer learning is a popular machine learning technique that aims to help with repetitive tasks by using an existing model. When it comes to situations where labelled data are only available in a source domain, Domain Adaption (DA), is a common technique to transfer learning. A small change or domain shift, due to illumination, pose, and image quality, between the source and target domains can lead to the degrading performance of machine learning models. Domain adaption (DA) provides an opportunity to mimic the human vision system which allows it to perform new tasks in a target domain by using the labelled data from a or more relevant source domains. Several research studies have recently addressed the issue of domain shift [7-9].

To implement CNN techniques, a large images dataset with manually labeled targets are required, which is expensive and challenging [7]. However, synthesizing images through use of the DA techniques can reduce the images need to be collected from the field and solve the problem when the labeled data cannot be acquired from the target domain [8]. Various research studies have been conducted on this concept, and have achieved promising results. Othman et al. [9] designed a domain adaption network to overcome the issues of domain shift in classification scenarios where the labeled images from the source domain and unlabeled ones from the target have different geographical features. Overall, when it comes to the problems of domain shift between source and target domains, the DA technique can not only reduce the costs of data preparation, but also improve image recognition.

AI Techniques from Vehicle Industry

Note: This section was published in my publication "Augmenting self-driving with remote control: Challenges and directions." and “Real-Time Vehicle Motion Detection and Motion Altering for Connected Vehicle: Algorithm Design and Practical Applications” before.

AI techniques are widely applied in many industries. In which, self-driving or autonomous vehicle has a significant connection with autonomous agriculture since the overlap of the core techniques between these two areas. Autonomous vehicle systems are being designed over the world with increasing success in recent years. This development makes autonomous farm system be realizable.

A self-driving vehicle is one that is capable of sensing its environment and navigating itself without human input. It uses a variety of techniques to sense its surroundings, such as LIDAR, RADAR, odometry, and computer vision. It uses these different sensor inputs to understand its environment, recognize various road conditions, traffic lights, road signs, lane boundaries, and track surrounding vehicles. The potential benefits of self-driving vehicles include increased safety, increased mobility and lower costs. For example, Google started its self-driving project in 2009, and has spent more than $1 billion in building and testing fully self-driving vehicles [10]. While legal and political challenges remain in its widespread adoption, there are also some technical bottlenecks on the way of developing completely reliable self-driving systems. All self-driving systems make decisions based on the perception of the environment and predefined traffic rules.

However, there has been occasional failures of these systems when they have encountered scenarios that were hitherto unseen. For instance, based on the situation in a construction zone, human drivers would realize that it is permissible to cross over a double yellow line by following the appropriately placed cones (which otherwise is illegal to cross in the US), while a self-driving vehicle may not be able to do so, and therefore be unable to move forward. Similarly, in poor weather conditions or due to traffic light malfunctions, the cues from different sensors may contradict each other leading to confusion in decision making.

Vehicle motion detection is always the focus of transportation research. Most of the conceptive methods are based on high-end sensors. Multiple external sensors, like microphone, accelerometer, and radio, are demonstrated to detect the motion and status of traffic. The driving status associated with crash is analyzed with real-time trip data to recognize a potential accident. Microsoft has designed a system to detect traffic honking, road bumps, and brakes with external sensors [11]. Dang-Nhac et al. [12] focus on driving activity detection and driving events recognition via addressing a new approach to optimize data window size and overlapping ratio for every single vehicle for training model purpose.

Various techniques and methods of detecting overtaking have been researched. [13] has promoted a system that used GPS and phones to detect acceleration and deceleration to estimate the congestion. A mixed algorithm was created to detect the acceleration combining dynamic planning with robust information. A wireless sensor networks layout was designed to monitor vehicles [14]. Moreover, the future motion was predicted using dynamic and kinematic models making certain control inputs, vehicle capabilities, and external situation related to the updating status of vehicles [15-16].

Any connected safety applications are less meaningful without widely applied in most vehicles. However, full-scaled vehicle motion detection is a challenging task and a long-term issue in mixed traffic of automated and manual vehicles. First, there is hardly a common standard device that was approved as an accurate detector. Second, as a result of diverse car manufactories and cost of communication devices, it will take a long time to make an agreement on the popularization of the same model device. For example, the most common devices are loop detectors, magnetic sensors, acoustic sensors, and computer vision techniques. However, these techniques require special hardware to be installed either on the infrastructures or in vehicles. This also limits the wide application and scalability because of the high cost.

Summary

In this review, several innovative methods and associated system were created for agriculture navigation, mapping, object detection and related vehicles technologies. These are referred by author's previous works [17-34]. Based on the experiences with these applications, it is believed all the addressed AI techniques will be useful to the development of future "smart farms." Autonomous and precision agricultural systems mitigate issues of current agriculture. This system is designed to reduce labor issues for the most dangerous and tedious agronomic tasks, improve efficiency, and reduce environmental impacts through better utilization of crop inputs. With the development of computing infrastructure, hardware, and improving algorithms, this system can enable more powerful applications in the future.

The utilization of SLAM and the assumption of the planar Mesh-map are based on the premise that the testing land is planar. Thus, the adoption of SLAM to better serve the navigation problem could still be improved. Other than IMU sensors, more growing status monitoring sensors could be added to detect other context information to boost the performance. These are imagined making SLAM a viable option for automated mapping and navigation systems to enable autonomous agricultural systems. Data association process could be improved in the future, which is implemented in this proposed approach. Although these systems outperform existing methods, they still failed to extract useful features from the images under adverse weather conditions during the data collection process.

Acknowledgment

This report is a review of some previous AI related work the author has participated.

References

[1]. Van Evert F, van der Voet P, Van Valkengoed E, Kooistra L, Kempenaar C (2012) Satellite-based herbicide rate recommendation for potato haulm killing. Eur J Agron 43:49–57

[2]. Basso B, Ritchie JT, Cammarano D, Sartori L (2011) A strategic and tactical management approach to select optimal N fertilizer rates for wheat in a spatially variable field. Eur J Agron 35:215–222

[3]. Basso B, Sartori L, Cammarano D, Grace PR, Fountas S, Sorensen C (2012) Environmental and economic evaluation of N fertilizer rates 1 in a maize crop in Italy: a spatial and temporal analysis. Biosyst Eng 113:103–111

[4]. Habib, A., Han, Y., Xiong, W., He, F., Zhang, Z., & Crawford, M. (2016). Automated ortho-rectification of UAV-based hyperspectral data over an agricultural field using frame RGB imagery. Remote Sensing, 8(10), 796.

[5]. Hunt, E. R., Cavigelli, M., Daughtry, C. S., et al. “Evaluation of digital photography from model aircraft for remote sensing of crop biomass and nitrogen status,” Precision Agriculture 6 (2005): 359-378.

[6]. Rieke, M., Foerster, T., Geipel, J., et al. “High-Precision Positioning And Real-Time Data Processing Of Uav-Systems,” International Archives of Photogrammetry Remote Sensing and Spatial Information Sciences 38 (2011): 1-C22.

[7]. Krizhevsky, A., Sutskever, I., Hinton. G. E., “Imagenet classification with deep convolutional neural networks,” 25th International Conference on Neural Information Processing Systems (2012).

[8]. Richter, S. R., Vineet, V., Roth, S., et al. “Playing for data: Ground truth from computer games,” European Conference on Computer Vision (2016).

[9]. Othman, E., Bazi, Y., Melgani, F, et al. Domain adaptation network for cross-scene classification. IEEE Transactions on Geoscience and Remote Sensing 55.8 (2017): 4441-4456.

[10]. Daily, M., [n. d.]. http://www.dailymail.co.uk/sciencetech/article-4889594/Google-s-spent-1-1-BILLION-self-driving-cars. html. ([n. d.]).

[11]. Bruwer, F. J., Booysen, M. J., “Comparison of GPS and MEMS support for smartphone-based driver behavior monitoring,” IEEE Symposium Series on Computational Intelligence (2015): 434-441.

[12]. Kyungmin, L., David, C., Eduardo, C., et al. “Outatime: Using speculation to enable low-latency continuous interaction for mobile cloud gaming,” In MobiSys. ACM. (2015).

[13]. Nie, Qifan, P. Shane Crawford, Andrea Bill, Steven T. Parker, Andrew J. Graettinger, Randy K. Smith, Terry B. Elliot, and E. Neal Paschal. "Electronic crash reporting: Implementation of the Model Minimum Uniform crash Criteria (MMUCC) and crash record life cycle comparison." Transportation Research Interdisciplinary Perspectives 9 (2021): 100318.

[14]. Lefèvre, S., Vasquez, D., Laugier, C., “A survey on motion prediction and risk assessment for intelligent vehicles,” ROBOMECH J. 1 (2014): 1–14.

[15]. Nie, Qifan, Pezhman Sheinidashtegol, Aibek Musaev, and Andrew J. Graettinger. A Social Media-Machine Learning Approach to Detect Public Perception of Transportation Systems. No. 19-05908. 2019.
[16]. Liu, Jun, Alexander Hainen, Xiaobing Li, Qifan Nie, and Shashi Nambisan. "Pedestrian injury severity in motor vehicle crashes: an integrated spatio-temporal modeling approach." Accident Analysis & Prevention 132 (2019): 105272.
[17]. Zhao, Wei, Xuan Wang, Bozhao Qi, and Troy Runge. "Ground-level Mapping and Navigating for Agriculture based on IoT and Computer Vision." IEEE Access 8 (2020): 221975-221985.
[18]. Hao, Yanping, Liangjie Xu, Bozhao Qi, Teng Wang, and Wei Zhao. "A machine learning approach for highway intersection risk caused by harmful lane-changing behaviors." In CICTP 2019, pp. 5623-5635. 2019.
[19]. Zhao, Wei, William Yamada, Tianxin Li, Matthew Digman, and Troy Runge. "Augmenting Crop Detection for Precision Agriculture with Deep Visual Transfer Learning—A Case Study of Bale Detection." Remote Sensing 13, no. 1 (2021): 23.
[20]. Zhao, W., Xu, L., Bai, J., Ji, M., & Runge, T., “Sensor-based risk perception ability network design for drivers in snow and ice environmental freeway: a deep learning and rough sets approach,” Soft computing 22.5 (2018): 1457-1466.
[21]. Qi, Bozhao, Wei Zhao, Haiping Zhang, Zhihong Jin, Xiaohan Wang, and Troy Runge. "Automated traffic volume analytics at road intersections using computer vision techniques." In 2019 5th International Conference on Transportation Information and Safety (ICTIS), pp. 161-169. IEEE, 2019.
[22]. Zhao, Wei, Liangjie Xu, and Bin Sun. "Relationship between vehicle emissions and air quality within a transfer center area of downtown: a case in wuhan, china." In CICTP 2015, pp. 3408-3418. 2015.
[23]. Wang, Wenmin, Wei Zhao, Xiaohan Wang, Zhihong Jin, Yuanchen Li, and Troy Runge. "A low-cost simultaneous localization and mapping algorithm for last-mile indoor delivery." In 2019 5th International Conference on Transportation Information and Safety (ICTIS), pp. 329-336. IEEE, 2019.
[24]. Wang, Tao, Liangjie Xu, Guojun Chen, and Wei Zhao. "A guidence method for lane change detection at signalized intersections in connected vehicle environment." In 2019 5th International Conference on Transportation Information and Safety (ICTIS), pp. 32-38. IEEE, 2019.
[25]. Zhao, W., Xu, L., Bai, J., Ji, M., Runge, T., “Sensor-based risk perception ability network design for drivers in snow and ice environmental freeway: A deep learning and rough sets approach,” Soft computing 22.5 (2018) 1457-1466.
[26]. Qi, Bozhao, Wei Zhao, Xiaohan Wang, Shen Li, and Troy Runge. "A low-cost driver and passenger activity detection system based on deep learning and multiple sensor fusion." In 2019 5th International Conference on Transportation Information and Safety (ICTIS), pp. 170-176. IEEE, 2019.
[27]. Zhao, Wei, Liangjie Xu, Zhijie Sasha Dong, Bozhao Qi, and Lingqiao Qin. "Improving transfer feasibility for older travelers inside high-speed train station." Transportation Research Part A: Policy and Practice 113 (2018): 302-317. Harvard
[28]. Kang, L., Zhao, W., Qi, B., and Banerjee, S., “Augmenting self-driving with remote control: Challenges and directions,” 19th International Workshop on Mobile Computing Systems & Applications.
[29]. Qi, B., et al., “DrivAid: Augmenting driving analytics with multi-modal information,” IEEE Vehicular Networking Conference (2018).
[30]. Zhao W., et al., “Vivid: Augmenting Vision-Based Indoor Navigation System with Edge Computing,” IEEE Access 8 (2020): 42909-42923.
[31]. Zhao, W., Yin, J. T., Wang, X. H., et al. “Real-Time Vehicle Motion Detection and Motion Altering for Connected Vehicle: Algorithm Design and Practical Applications,” Sensors (Basel) 19.19 (2019): 4108.
[32]. Wang X., et al., “Temporal Frame Sub-Sampling for Video Object Tracking,” Journal of Signal Processing Systems (2019): 1-13.
[33]. Zhao, W., Wang, W., Wang, X., Jin, Z., Li, Y., adn Runge, T., “A low-cost simultaneous localization and mapping algorithm for last-mile delivery,” ICTIS. IEEE (2019).
[34]. Zhao, W., Xu, L. J., Xi, S. X., et al. “A Sensor-Based Visual Effect Evaluation of Chevron Alignment Signs’ Colors on Drivers through the Curves in Snow and Ice Environment,” Journal of Sensors (2017): 9168525.