FRONTIER: AUTONOMY IN DETECTION, ACTUATION, AND PLANNING FOR ROBOTIC WEEDING SYSTEMS

P. Pandey, Hemanth Narayan D., S. N. Young

HIGHLIGHTS

- Recent research and development efforts center around developing smaller, portable robotic weeding systems.
- Deep learning methods have resulted in accurate, fast, and robust weed detection and identification.
- Additional key technologies under development include precision actuation and multi-vehicle planning.

Keywords. *Artificial intelligence, Automated systems, Automated weeding, Weed control.*

Weeds are a persistent and significant problem in agricultural production. Weeds, which tend to grow and produce very rapidly, compete with crops for critical resources, which can significantly reduce crop yields (Zimdahl, 2007). Herbicides are one of the most common and inexpensive approaches to controlling weeds; however, their continued and widespread use has prompted concerns due to off-target movement and steadily rising herbicide-resistant weed populations (Westwood et al., 2018). Given the significance of increasing herbicide-resistant weed populations and economic pressures to reduce costs associated with weeding, there is a need to implement more sustainable weed management approaches.

Integrated weed management (IWM) is an approach that combines multiple tactics, including genetic, biological, chemical, ecological, and mechanical approaches, for controlling weeds (Harker and O'Donovan, 2013; Pittman et al., 2020). The principle of IWM suggests that any one of these approaches, when used alone, will not result in optimized weed control; instead, development and application of multiple tactics is necessary. Further, Young (2018) argues that IWM is a continuum, and that "true IWM" requires integrating plant ecological and biological knowledge with technological machinery and algorithm-based decision making to respond to changes in weeds and the environment. To achieve this precise and specific integrated weed management paradigm, autonomous weeding systems will likely play a critical role (Young et al., 2017).

Submitted for review on 8 May 2020 as manuscript number ITSC 14085; approved for publication as a Frontier Article by the Information Technology, Sensors, & Control Systems Community of ASABE on 28 December 2020.

The authors are **Piyush Pandey,** Graduate Student, **Hemanth Narayan Dakshinamurthy,** Graduate Student, and **Sierra N. Young,** Assistant Professor, Department of Biological and Agricultural Engineering, North Carolina State University, Raleigh, North Carolina. **Corresponding author:** Sierra Young, 151 Weaver Laboratories, Campus Box 7625, Raleigh, NC 27695; phone: 919-515-6740; e-mail: syoung2@ncsu.edu.

AUTONOMOUS WEEDING ROBOTS

To enable successful and autonomous weed control, robotic weeding systems must detect and identify weeds, remove or control the weeds, and navigate autonomously without damaging the crop. The extent to which a robot can perform these tasks autonomously, also referred to as the level of autonomy (LOA), depends on its ability to sense the environment, plan based on that environment, and act on the environment with the intent of reaching a specific goal without external control (Beer et al., 2014). Multiple taxonomies have been proposed for classifying LOA (Beer et al., 2014; Huang et al., 2005; Parasuraman et al., 2000), and most definitions rely on the required extent and frequency of human intervention to complete a task. Levels of autonomy can largely be categorized as remote control, human-assisted, human-delegated, or human-supervised (Sheridan, 1992; Young and Peschel, 2020), with the possibility of a single system representing multiple LOA categories across different tasks. For example, a system may be considered autonomous in its ability to detect and identify weeds but require human intervention regarding path planning or steering. Thus, it is not sufficient to classify whether or not a robotic weeding system is autonomous, but instead determine if the system can complete a task, or set of tasks, with some level of autonomy (Beer et al., 2014).

Fennimore et al. (2016) noted two key aspects to achieving automated weed control, including crop and weed detection and weed control actuators. This article also considers a third aspect, task and path planning, which is particularly necessary when dealing with robotic systems that include multiple vehicles. Thus, the following sections focus on recent advances in algorithmic and computational approaches for autonomy in three aspects of robotic weed control: (1) weed detection and identification, (2) weed control actuators, and (3) task and path planning, and include systems that may still be in early exploration and development stages.

Vol. 64(2): 557-563 ISSN 2151-0032 https://doi.org/10.13031/trans.14085

Autonomous Weed Detection

Deep Learning for Weed Detection and Identification

An important aspect of developing an autonomous weed control robot is the development of fast and accurate methods to distinguish weeds from crops using computer vision. This problem can be approached in two ways: the first method includes the identification of crops to obtain a crop/non-crop discrimination, and the second method identifies the weeds themselves, often with species-level classification. Deep learning models, such as convolutional neural networks (CNNs), have emerged as dominant models in computer vision tasks. Image classification and object detection models based on CNNs have been successfully implemented for weed discrimination and species identification (Olsen et al., 2019; Yu et al., 2019). The primary advantage of deep learning models is that they make segmentation and feature selection redundant because the extraction of features and the mapping of learned features to an output result are developed during the network training process. Comparisons of deep learning models to methods using hand-crafted features (e.g., shape, color, texture) generally find that deep learning models result in higher classification accuracies (dos Santos Ferreira et al., 2017). In scenarios when feature-based models provide comparable classification results, the convenience of not manually crafting input features for model development is an advantage of CNN models. CNNs also have the ability to handle images with occlusion, unlike classification methods that use shape features (Dyrmann et al., 2017).

However, the requirement for a large amount of training data is a major challenge in using CNN models for weed detection. A technique available to mitigate this problem is data augmentation, in which transformed versions of the available images are used as additional data (dos Santos Ferreira et al., 2017). Image transformations may include rotation, scaling, illumination shifting, color shifting, and flipping, among others. By applying transformations to existing images of weeds, the variability of images from agricultural fields can be overcome, and overfitting can be reduced. For example, Olsen et al. (2019) applied data augmentation techniques to their large dataset, DeepWeeds, that consisted of 17,509 labeled images of eight different weed species found in Australian rangelands. In addition to data augmentation, simulated image data may also be used for model training, and weed detection CNN models trained solely on simulated data can perform just as well as models trained on real labeled images (Dyrmann et al., 2016). Another technique for reduction of the labeling effort is to take advantage of the spatial distribution of crop rows to obtain an initial classification. The results can then be used as "labeled data" for training more discerning models (Lottes and Stachniss, 2017; Louargant et al., 2018; Pérez-Ortiz et al., 2015). This approach demonstrates how the strength of well-developed algorithms, such as those for row detection, can be leveraged while implementing newer computer vision techniques.

Another approach to reduce the amount of labeled data needed for deep learning model training is to use transfer learning methods for weed classification, which is the practice of using pre-trained models for the initialization of CNN filters. Pre-trained CNN models have been used for recognition of weeds in cereals (Dyrmann et al., 2017), rice (Ma et al., 2019), and cotton and tomato (Espejo-Garcia et al., 2020). The use of previously trained models is useful in weeding applications where data availability is limited because this approach can be successful even if the model was pre-trained on completely different data (Oquab et al., 2014).

Model Processing Speed

While classification accuracy is arguably the most important performance parameter for weed identification applications, the model processing speed is also critically important for real-time weeding operations. Processing speed is largely dependent on model complexity, model implementation, and hardware. Processing rates of over 10 frames per second (fps) have been achieved using the low-cost and popular Raspberry Pi computer (Cambridge, U.K.) to deploy real-time application of deep learning models (Chechliński et al., 2019). Several common NVIDIA (Santa Clara, Cal.) graphics processing units (GPUs) have achieved deep learning model processing times over 20 fps; however, with reduced GPU power, lighter and less accurate models are required to achieve the same inference speeds (Partel et al., 2019). While GPUs generally have higher parallel computing power and performance compared to other processing devices (e.g., CPUs), they remain relatively high-power devices. A promising technology for deploying deep learning models for weed detection is the field-programmable gate array (FPGA), which can achieve significant decreases in power consumption while performing inference on weed images over 2× faster compared to baseline full-precision GPU implementation with little loss in accuracy (Lammie et al., 2019). Additionally, FPGA devices are useful in weed identification because the computations involved in prediction using a CNN model are well suited to acceleration through an FPGA implementation (Abdelouahab et al., 2018). This is an especially relevant and exciting direction of research because the computational power of mobile devices that can be carried by a weeding robot are limited in both processing speed and energy consumption.

Crop Design Principles for Weed Sensing

In addition to the advances in sensing and computer vision, robotic weeding applications based on the principle of "crop design" (van Herck et al., 2020) have also been presented in recent years. The reasoning behind this approach is that the crops and the field can be modified to accommodate the capabilities of existing robotic systems. Raja et al. (2019) presented several methods for facilitating crop-weed discrimination, including applying systemic markers to the seed or seedling, using signaling in transgenic plants (e.g., tomato plants with purple foliage), plant labels, and topical application of markers during transplanting. A study using machine-detectable markers on lettuce and tomato plants found an increase in weed removal rates when these markers were used with intelligent cultivators available in the market (Kennedy et al., 2020). These methods greatly facilitate the identification of crops, although they are not useful for the identification of individual species in their current form. However, as robotic systems develop, modifications to crops aimed at facilitating autonomous weeding can be expected.

Practical Considerations

An important consideration for a weed identification method designed for real-time deployment is the model inference time. The required processing rate depends on the desired speed of the weeding robot, the rate of image acquisition, and the field of view (FOV) of the imaging device. Olsen et al. (2019) presented an analysis for a system moving at 10 km h^{-1} where the FOV of the camera was 450 mm × 280 mm. They estimated a required processing rate of 10 fps to capture and process a new frame in time, given the vehicle's speed. This requirement was satisfied when the model was implemented on a GPU device (accuracy = 95%), and the inference speed was well beyond the required minimum when the model was implemented on an FPGA (accuracy = 94%) (Lammie et al., 2019). A useful observation from that study was the relatively unchanged value of accuracy accompanied by a significant gain in processing speed when the resolution of the input images was reduced. On the other hand, ensuring a certain speed for the weeding robot while ignoring the area covered by the images is not a realistic estimation for the speed of the overall system. For example, the total area captured in an hour while moving at 10 km h^{-1} using an image measuring 450 mm laterally is only 4,500 m^2. The area covered by the image acquisition system can be increased by using multiple cameras, but this comes with increased processing time and the need for an efficient design of multiple weed control actuators. To summarize this section, the careful tuning of the image data, the inference model, and adequate hardware are prerequisites for a successful real-time weed identification system.

Autonomous Weed Control Actuators

Inter-Row Weed Control

While the speed of an autonomous weed removal robot is largely dependent on the speed of the real-time weed detection method, the speed of the weed control actuator also impacts performance. Most of the weed removal techniques employed by autonomous systems are chemical or mechanical in nature and are used for either inter-row weeding (between the crop rows) or intra-row weeding (between the crop plants within a row) (Ahmad et al., 2014; Fennimore et al., 2016). Inter-row mechanical cultivation is a widely used approach for controlling weeds because the tools can be low-tech and non-selective. The cultivation tools are normally tractor-pulled implements (Peruzzi et al., 2017); however, more recently, smaller form-factor robotic systems have been developed to autonomously guide passive cultivation tools, such as the Dino and Oz robots by Naïo Technologies (Escalquens, France). While these systems are non-selective in weed removal, an advantage is that they remove the human operational requirements due to autonomous GPS-based navigation capabilities.

Intra-Row Weed Control

Compared to inter-row weeding, automated and precise intra-row weed control is a more challenging problem (Ahmad et al., 2014). Several technologies for automated intra-row weeding are commercially available. These technologies use features of the crop and row pattern to identify individual plants for directing mechanical tools (e.g., torsion weeders, knives, etc.) away from each crop plant as needed. Examples include the Robovator (F. Poulsen Engineering, Denmark) and the Garford Robocrop InRow Weeder (Peterborough, U.K.). However, these systems are often only successful in transplanted crops with sufficient plant spacing and size differential between weeds and crop plants, and while they may be autonomous in weed control actuation, they still require human-operated machinery to pull the implements (Peruzzi et al., 2017). Thus, challenges remain in achieving precise, autonomous intra-row weed control in sown crops with smaller spacing. Michaels et al. (2015) began to address this problem by developing an automated weed "stamper" to push small weeds into the soil, which controls weeds by limiting their photosynthesis and access to water. The system used a vision-based control approach to actuate a 10 mm diameter stamping mechanism and killed young weeds at a rate of up to two weeds per second (Langsenkamp et al., 2014; Michaels et al., 2015). While this rate is likely insufficient for deployment at commercial scale, the proof-of-concept system resulted in positional accuracy of the stamping tool within 2 mm and is a promising approach for precise and targeted intra-row weed control.

For chemical control approaches, autonomous see-and-spray systems require actuation of individual nozzles to apply a precise amount of herbicide only to weeds. The precision and accuracy of a spray system is dependent on the nozzle control, number of nozzles, nozzle design, and speed of the vehicle, with systems capable of targeting individual weeds with centimeter-level precision (Chostner, 2017; Utstumo et al., 2018). A potential advantage of precise see-and-spray systems is that they can provide intra-row weed control in cropping systems where mechanical approaches may not be feasible due to lack of space between crop plants. For example, Blue River's weed control technology, currently being developed for use in cotton, can achieve spray accuracy of 2.5 cm to target individual plants at speeds ranging from 1.8 to 3.5 m s^{-1} (Chostner, 2017) and can be used for both inter-row and intra-row weed control. Utstumo et al. (2018) developed a drop-on-demand (DoD) herbicide system in which the herbicide application is controlled down to individual droplets, using a ground robot to selectively shoot herbicide droplets onto detected weed leaves at a speed of 0.8 m s^{-1}. Their system was successful in developing a DoD treatment with well-formed droplets and high leaf retention for use in an autonomous see-and-spray robot, although testing was limited to four weed species.

Robotic systems that use both mechanical and herbicide weed control methods have also recently been explored. The AgBot II is a prototype for a modular crop and weed management robot developed by researchers at Queensland University of Technology in Australia. This system uses computer vision techniques and a lighting module to identify and classify plants and weed species, after which the system initiates weed removal with either mechanical implements, a precision spray system, or a combination of both, according to the species detected at a speed of 1.4 m s^{-1} (Bawden et al., 2017). Similarly, a ground vehicle developed by the European Robot Fleet for Highly Effective Agricultural and Forestry Management (RHEA) project was equipped with precision burners for real-time intra-row weed control in combination with mechanical inter-row cultivation tools for use in maize (Gonzalez-de-Santos et al., 2017). The researchers found that their system effectively controlled weeds without affecting yield.

Practical Considerations

As with weed detection and identification, achieving adequate speed in the control system for the weed removal actuator remains a barrier to achieving the efficiency and productivity levels needed for implementation. Currently, most systems use weed control actuators that require on-off or open-close control. As mechanical degrees of freedom (DoF) increase, achieving timely control of the implement can become difficult. For example, Bawden et al. (2017) calculated that a 2 DoF mechanical implement that could slide sideways and move vertically would require the sliding mechanism to achieve impractical linear speeds for implementation at a vehicle speed of 0.8 m s^{-1}. Additionally, the directed nozzle developed for the Ladybird platform used an inverse kinematic control approach combined with an optimization step and achieved an average total time of 0.52 s to spray each target (Underwood et al., 2015), which is similar to the ~1.75 weeds per second rate of the mechanical stamping system and visual servoing method developed by Michaels et al. (2015). The desired speed of the actuator also depends on the number and type of actuators, vehicle speed, and desired weeding performance, although faster actuation to control a larger number of weeds in the same amount of time is generally a reasonable goal during development. While there are computational and control approaches that may help achieve faster actuation for manipulators (e.g., Lin et al., 2019), another promising strategy to increase throughput is to mount multiple actuators to a single robot, or to use multiple robots in the field to parallelize weeding tasks, strategies for which are described below.

Vehicle Route and Task Planning

To be economically effective, an autonomous weed removal system must adequately and efficiently achieve spatial coverage within a field (Lowenberg-DeBoer et al., 2020). For a single autonomous weeding robot, a coverage path must be generated to ensure that the system optimally covers the target area, which is largely considered a solved problem, although exceptions exist. However, when multiple robots are considered, each robot must be assigned to perform tasks so that the overall performance is maximized given a set of constraints, which remains an open research question. Generating trajectories for groups of cooperative or collaborative robots for autonomous weed control presents a challenge due to changing environmental conditions, broken or limited communication links, actuation limitations, and the physical row constraints of field crops, but recent advances have resulted in path planning and task allocation methods for agricultural robots that attempt to overcome those challenges, which are described below.

The task allocation problem for automated weeding is determining the time, place, and robot for performing weeding tasks within a given field. Task planners can generally be either offline, where information about the mission is used to generate task assignments for each robot *a priori*, or online, where the task planner may adapt to new information and new situations during a mission. Task planners may also be centralized, in which one central planner maintains a connection with and allocates tasks to all agents, or decentralized, in which the task planning tasks are distributed between all robots within the system; additionally, there are hybrid centralized-decentralized approaches. Central planners are generally able to more effectively allocate tasks to multiple robots, but reliance on connectivity and potential connectivity loss between the planner and individual robots remains a challenge, in addition to the lack of robustness against failure of the planner.

Distributed real-time task planners can help overcome these issues. Middleware entities can facilitate task planning between multiple distributed robots by enabling queries and information sharing between individual systems that are necessary for task matching and assignment (Drenjanac et al., 2014). Additionally, dynamic decomposition algorithms have been developed that support dynamic portioning to enable field areas assigned to individual robots to update during the mission based on learned information, for example, of impassable areas (Drenjanac et al., 2014). An optimization approach may also be used that seeks to maximize a reward metric across multiple vehicles. For weeding robots, a coordinated planner was developed that maximized the height of visited weeds by multiple vehicles (McAllister et al., 2019). This method also evaluated different levels of information sharing, finding that more information sharing between robots resulted in higher total reward for the planner. Other distributed planners use only local information on each robot, which does not require an inter-robot communication link but may lead to inefficiencies (Janani et al., 2016). However, the redundancy against communication and single-robot failures makes these approaches appealing for agricultural settings that may have limited network connectivity.

The Mobile Agricultural Robot Swarms (MARS) project aims to drive a paradigm shift in farming by using large groups of small, distributed robots for completing agricultural tasks, which requires coordinated planning (Blender et al., 2016). The MARS effort includes the development of a robot as well as communication and software architectures to facilitate multi-vehicle planning; this includes a central entity to manage the robot swarm, named OptiVisor, which deploys both coverage planning and control optimization algorithms. OptiVisor also interfaces between the robots and the cloud, which is used for user inputs regarding settings and instructions for the system. There are two proposed architectures, one that enables OptiVisor deployment on a local computer near the field, and another with planning outsourced to the cloud (remote) and control running locally (at the field), both of which enable planning and re-planning during a mission. Although the MARS system is currently being designed for seeding tasks, the swarm control and planning approach that achieves coverage within a field could be used for weeding with modified robots.

Practical Considerations

While real-time planning and re-planning can overcome practical challenges that arise in the field, a recent review by Santos et al. (2020) noted that most of the current algorithmic approaches for path planning in agriculture are offline approaches. This is likely because path planning approaches require computationally intensive methods, such as heuristics and meta-heuristics, for finding an approximately optimal solution when exact solutions are computationally infeasible (Raja and Pugazhenthi, 2012). As noted by Seyyedhasani et al., (2019), field coverage planning in agricultural operations can be unpredictable due to weather, machinery breakdowns, and field conditions, leaving offline-only computational approaches unusable. Approaches that are being explored to overcome the computational challenges of multi-vehicle coverage planning include making algorithm recommendations based on field and vehicle characteristics (Seyyedhasani et al., 2019), using fast, dynamic path-planning formulations that can continually adjust and assign new goals and paths (Han and Yu, 2020), and algorithm modifications and improvements to increase the convergence speed of existing heuristics (Dai et al., 2019).

Summary and Outlook

Approximately a decade ago, robust weed detection and identification were identified as the primary obstacle to commercial development of robotic weed control technology (Slaughter et al., 2008). Since then, key advances in computer vision and sensing have enabled accurate weed detection in real-time. Even more important are the recent developments in weed identification using deep learning, which has been facilitated by the availability of vast computing resources and the ubiquity of digital imaging (dos Santos Ferreira et al., 2017; Olsen et al., 2019). While most deep learning applications require the availability of large, labeled data sets, strategies for reducing and eliminating this bottleneck are being explored, including development of open-source datasets and transfer learning methods (Dyrmann et al., 2017; Espejo-Garcia et al., 2020; Ma et al., 2019). The advances and high accuracies of machine learning-based approaches for autonomous weed detection and identification indicate that weed detection and identification may no longer be considered the primary obstacle to commercialization of robotic weed removal systems, although work is still needed to make existing CNN models more generalizable across a broader range of crops, weeds, and geographic locations, a problem that has been recognized in theoretical studies on CNNs (Azulay and Weiss, 2019; Long and Sedghi, 2019).

The other two aspects discussed in this article, autonomous weed control actuation and vehicle route and task planning, remain active areas of research. Actuation approaches that require on-off or open-close control currently achieve higher speeds of operation (Bawden et al., 2017; Chostner, 2017) but are less precise than targeted and directed actuators that mechanically or chemically remove individual weeds (Michaels et al., 2015; Utstumo et al., 2018). The computational time required to solve positional and steering control problems (e.g., inverse kinematics, visual servoing) must decrease for precision approaches to become viable. Another approach to increasing the throughput of these precision actuation approaches is to include multiple actuators on a single machine and/or deploy multiple machines. For the latter, efficient and dynamic task and route planning are required so that multiple machines can adequately cover the entire field. Improving vehicle connectivity and reducing communication failures between multiple robots must also be achieved to enable online planning, likely through the development of algorithms that do not over-rely on inter-vehicle communication (Janani et al., 2016) and are robust against failure (Bechon et al., 2020), or the creation of new communication networks (Yaacoub and Alouini, 2019).

In-field testing and evaluation of robotic weeding systems are required across a wider range of crops and weed conditions, including weed species, growth stages, and densities, to evaluate their efficacy without damaging the crop or affecting harvest (Lati et al., 2016; Melander et al., 2015). Further, as field trials for the efficacy of these wide varieties of weed control systems increase, another emerging aspect ripe for automation is the *a priori* and in-field selection of appropriate weed control tools. The weed-specific approach reported by Bawden et al. (2017) that either mechanically or chemically removes weeds is highly relevant when weed populations include a subset of herbicide-resistant species.

While there has been progress in developing weeding robots with autonomous capabilities, challenges remain regarding their widespread use and success across multiple crops and weed species. As Merfield (2016) noted, many other tasks are associated with weed management beyond the weed detection, control actuation, and navigation tasks considered here. These additional tasks include monitoring crop, weed, and soil conditions to determine when weeding should occur, selecting an appropriate set of weeding tools, and monitoring weeder performance in real-time to ensure proper operation. Real-time adjustments of the weed control actuator are also necessary to adapt to changes in weed, soil, and crop conditions that can affect performance (Merfield, 2016). Ultimately, autonomous weeding is a dynamic, complex task that requires developing systems that are autonomous across all aspects and that can selectively and precisely control weeds at the species level. This would enable advancement from a low-level IWM approach to a "true IWM" approach when integrated with other weed control methods (Young, 2018).

Acknowledgements

This work was supported by Cotton Incorporated (Award No. 19-535) and the USDA National Institute of Food and Agriculture (Hatch Project 1021499).

REFERENCES

Abdelouahab, K., Pelcat, M., Serot, J., & Berry, F. (2018). Accelerating CNN inference on FPGAs: A survey. Retrieved from https://arxiv.org/abs/1806.01683

Ahmad, M. T., Tang, L., & Steward, B. L. (2014). Automated mechanical weeding. In S. L. Young & F. J. Pierce (Eds.), *Automation: The future of weed control in cropping systems* (pp. 125-137). Dordrecht, Netherlands: Springer. https://doi.org/10.1007/978-94-007-7512-1_7

Azulay, A., & Weiss, Y. (2019). Why do deep convolutional networks generalize so poorly to small image transformations? *J. Machine Learning Res., 20*(184), 1-25.

Bawden, O., Kulk, J., Russell, R., McCool, C., English, A., Dayoub, F., ... Perez, T. (2017). Robot for weed species plant-specific management. *J. Field Rob., 34*(6), 1179-1199. https://doi.org/10.1002/rob.21727

Bechon, P., Lesire, C., & Barbier, M. (2020). Hybrid planning and distributed iterative repair for multi-robot missions with communication losses. *Autonomous Robots, 44*(3), 505-531. https://doi.org/10.1007/s10514-019-09869-w

Beer, J. M., Fisk, A. D., & Rogers, W. A. (2014). Toward a framework for levels of robot autonomy in human-robot interaction. *J. Human-Robot Interaction, 3*(2), 74-99. https://doi.org/10.5898/JHRI.3.2.Beer

Blender, T., Buchner, T., Fernandez, B., Pichlmaier, B., & Schlegel, C. (2016). Managing a mobile agricultural robot swarm for a seeding task. *Proc. 42nd Annual Conf. IEEE Industrial Electronics Society* (pp. 6879-6886). https://doi.org/10.1109/IECON.2016.7793638

Chechliński, Ł., Siemiątkowska, B., & Majewski, M. (2019). A system for weeds and crops identification: Reaching over 10 FPS on raspberry Pi with the usage of MobileNets, DenseNet, and custom modifications. *Sensors, 19*(17), 3787. https://doi.org/10.3390/s19173787

Chostner, B. (2017). See & spray: The next generation of weed control. *Resource, 24*(4), 4-5.

Dai, X., Long, S., Zhang, Z., & Gong, D. (2019). Mobile robot path planning based on ant colony algorithm with A* heuristic method. *Front. Neurorob., 13*, article 15. https://doi.org/10.3389/fnbot.2019.00015

dos Santos Ferreira, A., Matte Freitas, D., Gonçalves da Silva, G., Pistori, H., & Theophilo Folhes, M. (2017). Weed detection in soybean crops using ConvNets. *Comput. Electron. Agric., 143*, 314-324. https://doi.org/10.1016/j.compag.2017.10.027

Drenjanac, D., Tomic, S. D., Klausner, L., & Kühn, E. (2014). Harnessing coherence of area decomposition and semantic shared spaces for task allocation in a robotic fleet. *Info. Proc. Agric., 1*(1), 23-33. https://doi.org/10.1017/S2040470017000206

Dyrmann, M., Jørgensen, R. N., & Midtiby, H. S. (2017). RoboWeedSupport: Detection of weed locations in leaf-occluded cereal crops using a fully convolutional neural network. *Adv. Animal Biosci., 8*(2), 842-847. https://doi.org/10.1017/S2040470017000206

Dyrmann, M., Mortensen, A. K., Midtiby, H. S., & Jørgensen, R. N. (2016). Pixel-wise classification of weeds and crop in images by using a fully convolutional neural network. *Proc. CIGR AgEng Conf.* Retrieved from https://conferences.au.dk/uploads/tx_powermail/cigr2016paper_semanticsegmentation.pdf

Espejo-Garcia, B., Mylonas, N., Athanasakos, L., Fountas, S., & Vasilakoglou, I. (2020). Toward weed identification assistance through transfer learning. *Comput. Electron. Agric., 171*, article 105306. https://doi.org/10.1016/j.compag.2020.105306

Fennimore, S. A., Slaughter, D. C., Siemens, M. C., Leon, R. G., & Saber, M. N. (2016). Technology for automation of weed control in specialty crops. *Weed Tech., 30*(4), 823-837. https://doi.org/10.1614/WT-D-16-00070.1

Gonzalez-de-Santos, P., Ribeiro, A., Fernandez-Quintanilla, C., Lopez-Granados, F., Brandstoetter, M., Tomic, S., ... Kaplanis, G. (2017). Fleets of robots for environmentally safe pest control in agriculture. *Prec. Agric., 18*(4), 574-614.

Han, S. D., & Yu, J. (2020). DDM: Fast near-optimal multi-robot path planning using diversified-path and optimal sub-problem solution database heuristics. *IEEE Robotics Automat. Letters, 5*(2), 1350-1357. https://doi.org/10.1109/LRA.2020.2967326

Harker, K. N., & O'Donovan, J. T. (2013). Recent weed control, weed management, and integrated weed management. *Weed Tech., 27*(1), 1-11. https://doi.org/10.1614/WT-D-12-00109.1

Huang, H., Pavek, K., Albus, J., & Messina, E. (2005). Autonomy levels for unmanned systems (ALFUS) framework: An update. *Proc. SPIE, 5804*, 439-448. https://doi.org/10.1117/12.603725

Janani, A., Alboul, L., & Penders, J. (2016). Multi robot cooperative area coverage, case study: Spraying. *Proc. Annual Conf. Toward Autonomous Robotic Systems* (pp. 165-176). Dordrecht, Netherlands: Springer. https://doi.org/10.1007/978-3-319-40379-3_17

Kennedy, H., Fennimore, S. A., Slaughter, D. C., Nguyen, T. T., Vuong, V. L., Raja, R., & Smith, R. F. (2020). Crop signal markers facilitate crop detection and weed removal from lettuce and tomato by an intelligent cultivator. *Weed Tech., 34*(3), 342-350. https://doi.org/10.1017/wet.2019.120

Lammie, C., Olsen, A., Carrick, T., & Azghadi, M. R. (2019). Low-power and high-speed deep FPGA inference engines for weed classification at the edge. *IEEE Access, 7*, 51171-51184. https://doi.org/10.1109/ACCESS.2019.2911709

Langsenkamp, F., Sellmann, F., Kohlbrecher, M., Kielhorn, A., Wolfram, Strothmann, ... Trautz, D. (2014). Tube stamp for mechanical intra-row individual plant weed control. *Proc. 18th World Congress of CIGR* (pp. 16-19).

Lati, R. N., Siemens, M. C., Rachuy, J. S., & Fennimore, S. A. (2016). Intrarow weed removal in broccoli and transplanted lettuce with an intelligent cultivator. *Weed Tech., 30*(3), 655-663. https://doi.org/10.1614/WT-D-15-00179.1

Lin, P., Huang, H., & Huang, H. (2019). Analytical solution for inverse kinematics using dual quaternions. *IEEE Access, 7*, 166190-166202. https://doi.org/10.1109/ACCESS.2019.2953553

Long, P. M., & Sedghi, H. (2019). Generalization bounds for deep convolutional neural networks. Retrieved from https://arxiv.org/abs/1905.12600

Lottes, P., & Stachniss, C. (2017). Semi-supervised online visual crop and weed classification in precision farming exploiting plant arrangement. *Proc. IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems* (pp. 5155-5161). https://doi.org/10.1109/IROS.2017.8206403

Louargant, M., Jones, G., Faroux, R., Paoli, J.-N., Maillot, T., Gee, C., & Villette, S. (2018). Unsupervised classification algorithm for early weed detection in row-crops by combining spatial and spectral information. *Remote Sensing, 10*(5), article 761. https://doi.org/10.3390/rs10050761

Lowenberg-DeBoer, J., Huang, I. Y., Grigoriadis, V., & Blackmore, S. (2020). Economics of robots and automation in field crop production. *Prec. Agric., 21*(2), 278-299. https://doi.org/10.1007/s11119-019-09667-5

Ma, X., Deng, X., Qi, L., Jiang, Y., Li, H., Wang, Y., & Xing, X. (2019). Fully convolutional network for rice seedling and weed image segmentation at the seedling stage in paddy fields. *PLoS One, 14*(4), e0215676. https://doi.org/10.1371/journal.pone.0215676

McAllister, W., Osipychev, D., Davis, A., & Chowdhary, G. (2019). Agbots: Weeding a field with a team of autonomous robots. *Comput. Electron. Agric., 163*, article 104827. https://doi.org/10.1016/j.compag.2019.05.036

Melander, B., Lattanzi, B., & Pannacci, E. (2015). Intelligent versus non-intelligent mechanical intra-row weed control in transplanted onion and cabbage. *Crop Prot., 72*, 1-8. https://doi.org/10.1016/j.cropro.2015.02.017

Merfield, C. N. (2016). Robotic weeding's false dawn? Ten requirements for fully autonomous mechanical weed management. *Weed Res., 56*(5), 340-344. https://doi.org/10.1111/wre.12217

Michaels, A., Haug, S., & Albert, A. (2015). Vision-based high-speed manipulation for robotic ultra-precise weed control. *Proc. IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems* (pp. 5498-5505). https://doi.org/10.1109/IROS.2015.7354156

Olsen, A., Konovalov, D. A., Philippa, B., Ridd, P., Wood, J. C., Johns, J., ... White, R. D. (2019). Deepweeds: A multiclass weed species image dataset for deep learning. *Sci. Rep., 9*(1), article 2058. https://doi.org/10.1038/s41598-018-38343-3

Oquab, M., Bottou, L., Laptev, I., & Sivic, J. (2014). Learning and transferring mid-level image representations using convolutional neural networks. *Proc. IEEE Conf. on Computer Vision and Pattern Recog.* (pp. 1717-1724). https://doi.org/10.1109/CVPR.2014.222

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Trans. Syst. Man Cybernetics A, 30*(3), 286-297. https://doi.org/10.1109/3468.844354

Partel, V., Kakarla, S. C., & Ampatzidis, Y. (2019). Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. *Comput. Electron. Agric., 157*, 339-350. https://doi.org/10.1016/j.compag.2018.12.048

Pérez-Ortiz, M., Peña, J. M., Gutiérrez, P. A., Torres-Sánchez, J., Hervás-Martínez, C., & López-Granados, F. (2015). A semi-supervised system for weed mapping in sunflower crops using unmanned aerial vehicles and a crop row detection method. *Appl. Soft Comput., 37*, 533-544. https://doi.org/10.1016/j.asoc.2015.08.027

Peruzzi, A., Martelloni, L., Frasconi, C., Fontanelli, M., Pirchio, M., & Raffaelli, M. (2017). Machines for non-chemical intra-row weed control in narrow and wide-row crops: A review. *J. Agric. Eng., 48*(2), 57-70. https://doi.org/10.4081/jae.2017.583

Pittman, K., Flessner, M., Rubione, C., & Ackroyd, V. (2020). What is integrated weed management? Getting rid of weeds (GROW) through integrated weed management. Retrieved from growiwm.org

Raja, P., & Pugazhenthi, S. (2012). Optimal path planning of mobile robots: A review. *Intl. J. Phys.Sci., 7*(9), 1314-1320.

Raja, R., Slaughter, D. C., Fennimore, S. A., Nguyen, T. T., Vuong, V. L., Sinha, N., ... Siemens, M. C. (2019). Crop signalling: A novel crop recognition technique for robotic weed control. *Biosyst. Eng., 187*, 278-291. https://doi.org/10.1016/j.biosystemseng.2019.09.011

Santos, L. C., Santos, F. N., Pires, E. J., Valente, A., Costa, P., & Magalhães, S. (2020). Path planning for ground robots in agriculture: A short review. *Proc. IEEE Intl. Conf. on Autonomous Robot Systems and Competitions* (pp. 61-66). https://doi.org/10.1109/ICARSC49921.2020.9096177

Seyyedhasani, H., Dvorak, J. S., & Roemmele, E. (2019). Routing algorithm selection for field coverage planning based on field shape and fleet size. *Comput. Electron. Agric., 156*, 523-529. https://doi.org/10.1016/j.compag.2018.12.002

Sheridan, T. B. (1992). *Telerobotics, automation, and human supervisory control.* Cambridge, MA: MIT Press.

Slaughter, D. C., Giles, D. K., & Downey, D. (2008). Autonomous robotic weed control systems: A review. *Comput. Electron. Agric., 61*(1), 63-78. https://doi.org/10.1016/j.compag.2007.05.008

Underwood, J. P., Calleija, M., Taylor, Z., Hung, C., Nieto, J., Fitch, R., & Sukkarieh, S. (2015). Real-time target detection and steerable spray for vegetable crops. *Proc. Intl. Conf. on Robotics and Automation (ICRA 2015).* Piscataway, NJ: IEEE.

Utstumo, T., Urdal, F., Brevik, A., Dørum, J., Netland, J., Overskeid, Ø., ... Gravdahl, J. T. (2018). Robotic in-row weed control in vegetables. *Comput. Electron. Agric., 154*, 36-45. https://doi.org/10.1016/j.compag.2018.08.043

van Herck, L., Kurtser, P., Wittemans, L., & Edan, Y. (2020). Crop design for improved robotic harvesting: A case study of sweet pepper harvesting. *Biosyst. Eng., 192*, 294-308. https://doi.org/10.1016/j.biosystemseng.2020.01.021

Westwood, J. H., Charudattan, R., Duke, S. O., Fennimore, S. A., Marrone, P., Slaughter, D. C., ... Zollinger, R. (2018). Weed management in 2050: Perspectives on the future of weed science. *Weed Sci., 66*(3), 275-285. https://doi.org/10.1017/wsc.2017.78

Yaacoub, E., & Alouini, M.-S. (2019). A key 6G challenge and opportunity: Connecting the remaining 4 billions: A survey on rural connectivity. Retrieved from https://arxiv.org/abs/1906.11541

Young, S. (2018). Beyond precision weed control: A model for true integration. *Weed Tech., 32*(1), 7-10. https://doi.org/10.1017/wet.2017.70

Young, S. L., Pitla, S. K., Van Evert, F. K., Schueller, J. K., & Pierce, F. J. (2017). Moving integrated weed management from low level to a truly integrated and highly specific weed management system using advanced technologies. *Weed Res., 57*(1), 1-5. https://doi.org/10.1111/wre.12234

Young, S. N., & Peschel, J. M. (2020). Review of human-machine interfaces for small unmanned systems with robotic manipulators. *IEEE Trans. Human-Machine Syst., 50*(2), 131-143. https://doi.org/10.1109/THMS.2020.2969380

Yu, J., Arnold, W. S., Nathan, S. B., & Shaun, M. S. (2019). Deep learning for image-based weed detection in turfgrass. *European J. Agron., 104*, 78-84. https://doi.org/10.1016/j.eja.2019.01.004

Zimdahl, R. L. (2007). *Weed-crop competition: A review.* Hoboken, NJ: John Wiley & Sons.