A Literature Review of Non-Herbicide, Robotic Weeding:

A Decade of Progress

A review by:

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Abstract: *Weeds are one of the primary pests in agriculture production, with the number of herbicide-resistant weed populations on the rise. An integrated weed management approach that incorporates multiple strategies will be necessary moving forward to effectively manage weeds. Non-herbicide, autonomous, mechanical weed control will be a critical component in any integrated weed management program. Over the past decade, great progress has been made on the development of robotic weed control systems, particularly related to improved navigation, control, and artificial intelligence-based weed detection methods. Moving forward, research and development efforts into advancing automated weed control technologies will play a large part in shaping the future of weed control strategies. Understanding the current landscape of these research and development efforts is an important step in the weed control technology development process. This literature review provides an overview of progress made over the last decade (2010-2020) on robotics development specifically related to weed control, with a focus on relevant contributions from both academia and industry.*

INTRODUCTION

Weeds are a persistent and significant problem in agricultural production. In cropping systems, weeds compete with crops for critical resources such as light, nutrients, and water, which can significantly reduce crop yields; additionally, weeds tend to grow and produce seed very rapidly (Zimdahl, 1980). Current weed management approaches rely on large-scale herbicide use; however, this approach is becoming unsustainable due to environmental concerns from off-target movement and increases in herbicide-resistant weed populations. As reported by Westwood et al. (2018), no new herbicide mechanisms of action (MOAs) have been developed since the 1980s, and the number of herbicide-resistant weed populations have been steadily increasing since the 1970s. Given the significance of increasing herbicide resistant weed populations and economic pressures to reduce costs associated with hand weeding, there is a clear need to develop and implement more sustainable weed management approaches.

Integrated weed management (IWM) has been defined as an approach that combines multiple tactics, including genetic, biological, chemical, ecological, and mechanical approaches for controlling weeds (Swanton & Weise, 1991). Moving forward, it is unlikely that any one of these approaches when used alone will result in successful weed control, but rather the development and application of multiple strategies will be necessary, including the incorporation of automated mechanical and non-herbicide removal technologies. The development of mechanized and robotic weeding systems can provide sustainable alternatives to traditional herbicide application approaches for a wide range of crops and cropping systems; a notion that is especially true considering recent technological advancements and relatively low barriers of entry in the development of

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artificial intelligence, machine learning, and robotic software development.

Recent reviews have discussed non-herbicide machines and implements suitable for weed removal in organic and (Peruzzi et al., 2017), automated weed removal in specialty crops (Fennimore, Slaughter, Siemens, Leon, & Saber, 2016), and integrated weed management approaches that incorporate precision weed removal technologies (Gage & Schwartz-Lazaro, 2019; Young, 2012). Over the past decade there has been significant investment into research and development of robotics technology for automated weed removal, although some of this work has remained in a research environment and is not yet commercially available. Given this, the purpose of this review is to understand the current landscape and progress made in autonomous robotic weeding technologies over the last decade, with a focus on automation and artificial intelligence-related contributions from both academia and industry.

The remainder of this paper is organized as follows. First, an overview of computer vision approaches for detecting weeds is provided, including RGB imaging, segmentation, and thresholding. Next, a detailed survey of weed identification approaches is included, focusing on row identification and use of spatial with spectral features, followed by a discussion on machine learning and deep learning approaches. Then, field coverage approaches for weeding robots is presented, including both coverage planning and task allocation for multi-robot systems. Finally, field-ready robotic systems are discussed, including commercially available systems and systems that are near commercialization but still under development. The report concludes with a discussion on considerations for future robotic systems and identifies areas where further research is needed.

COMPUTER VISION APPROACHES FOR WEED DETECTION

Computer vision approaches generally deal with utilizing complex image processing techniques to extract meaningful features from a given set of images. The general method for weed detection using computer vision starts with the acquisition of a digital image that will typically contain weeds mixed with crops, as well as soil in the background. Subsquent image processing aims to pinpoint the location of weeds, such that the system can swiftly and precisely guide the weeding mechanism. In some cases, the machine vision system is also designed to be used for guiding the navigation system of the robot. Computer vision approaches have been widely and historically used for *post hoc* weed identification (El-Faki, Zhang, & Peterson, 2000; Mao, Wang, & Wang, 2003; Perez, Lopez, Benlloch, & Christensen, 2000), but there is still progress being made on computer vision techniques for identifying weeds in the field in real-time for robotics applications.

RGB Imaging

Acquiring RGB images in the field is the most economic computer vision method for weed detection and is commonly studied. Images may be acquired using handhld cameras, cameras mounted on a ground vehicle, or from a UAV (Gonzalez-de-Santos et al., 2017). In the case of weed detection, the objective of segmentation using RGB images is to segment the weed pixels and treat the crop and soil as background; however, weeds and crops have spectral properties that are indistinguishable in most cases, especially when the plants are young. Thus, weed discrimination algorithms typically first segment all vegetation pixels, followed by the classification of segmented pixels into crop and weed pixels. The addition of an NIR band to the RGB image acquisition is also found in some studies, which benefits the segmentation process.

For the first step of vegetation segmentation, spectral properties of vegetation are commonly used. The basic spectral property that can be exploited is the greenness of vegetation. The green channel in RGB color space cannot be directly used for this purpose since intensity values in the RGB color space are correlated with illumination. Therefore, the intensity values from more than one channel must be used to obtain color indices suitable for vegetation segmentation across varying illumination levels. In this approach, a grayscale image is created by combining two or more color channels. Finally, a threshold is used to create a binary image with vegetation and background pixels separated into two classes. Among several color indices that have been used for this purpose, the Excess Green Index (ExG) (Woebbecke, Meyer, Von Bargen, & Mortensen, 1995) is still found to be popular in recent weed detection literature (Guerrero, Pajares, Montalvo, Romeo, & Guijarro, 2012; Kargar & Shirzadifar, 2013). Segmentation of vegetation in field images is not a challenge unique to weed detection, and the techniques of spectral segmentation have been extensively studied. For example, Hamuda, Glavin, and Jones (2016) presented a detailed description of ExG and other color indices in their survey of methods for plant segmentation in field images.

In addition to the use of color indices derived from RGB channels, some studies in weed detection have converted the RGB images into YCrCb (J.-L. Tang, Chen, Miao, & Wang, 2016), HSV (Kargar & Shirzadifar, 2013) or L*a*b color spaces (Hall, Dayoub, Kulk, & McCool, 2017) in order to isolate the chromatic properties from illumination properties. Some studies have used artificial lighting in the field to create uniform illumination across images (Haug, Michaels, Biber, & Ostermann, 2014; Lottes, Hörferlin, Sander, & Stachniss, 2017; Sujaritha, Annadurai, Satheeshkumar, Sharan, & Mahesh, 2017). Shading can also be used to create an area of diffused light (Bakhshipour & Jafari, 2018; Haug et al., 2014; Lottes et al., 2017). Post processing methods, such as histogram equalization and contrast stretching, have also been used to deal with images collected under varying illumination (Liu, Lee, & Saunders, 2014; Siddiqi, Lee, & Khan, 2014).

Another challenge during segmentation using spectral properties is the masking of plant reflectance by foreign material; for example, masking can be caused by mud splattered onto leaves after rainfall or irrigation (Guerrero et al., 2012). To address this problem, Guerrero et al. (2012) used a combined vegetation index for initial segmentation followed by a support vector machine to retrieve vegetation pixels that may have been erroneously classified as background.

Use of NDVI

In studies that use multispectral cameras producing RGB+NIR images, Normalized Difference Vegetation Index (NDVI) is the preferred method for segmentation of vegetation pixels (Bakhshipour & Jafari, 2018; Haug et al., 2014; Lottes et al., 2017). NDVI is the normalized difference between intensities at NIR and red channels and is useful for segmentation because living vegetation has higher reflectance in the NIR region compared to the visible region. In their study for weed discrimination using UAV imagery, Lottes et al. (2017) found that while ExG gave the best results among RGB-based indices, segmentation based on NDVI produced better segmentation results compared to RGB-based indices. They reported that segmentation based on thresholding NDVI values performed better because of consistently higher reflectance of vegetation in the NIR region across different illumination levels. On the other hand, Potena, Nardi, and Pretto (2016) reported that selecting a reliable threshold while segmenting NDVI values can be challenging and proposed using a deliberately low threshold for initial segmentation followed by a convolutional neural network (CNN) model for removing any false positives that may result due to the low threshold value.

Thresholding

Selection of an appropriate threshold value for segmentation is a step that presents many alternatives. Otsu's method (Otsu, 1979) of finding the threshold value through grey-level histogram has been used by Gonzalez-de-Santos et al. (2017), Montalvo et al. (2012), Haug et al. (2014), Bakhshipour, Jafari, Nassiri, and Zare (2017), and García-Santillán and Pajares (2018). Although Otsu's method is popular in threshold detection tasks for plant images, several studies have reported it lacking in speed and accuracy for vegetation segmentation in real time (Burgos-Artizzu, Ribeiro, Guijarro, & Pajares, 2011; Milioto, Lottes, & Stachniss, 2018; Xu, Gao, Khot, Meng, & Zhang, 2018). Burgos-Artizzu et al. (2011) found that the use of mean intensity value as threshold made the process faster and more accurate. Milioto et al. (2018) reported that Otsu's method failed in images where vegetation pixels are underrepresented in the image. They also cited problems with adaptive thresholding and advocated the use of a learning-based approach combining the segmentation and classification steps. Xu et al. (2018) used a particle swarm optimum algorithm to determine the threshold and reported that Otsu's method was too slow for their real-time requirements.

ROW IDENTIFICATION

Once a binary image with a masked background is created, the next step is to identify the precise location of weeds and crops. For the classification of segmented vegetation into crops and weeds, several studies use the fact that crops in modern agriculture are planted in a regular pattern of rows. The problem is then reduced to one of row identification, after which all vegetation that does not belong to the detected rows can be classified as weeds. Burgos-Artizzu et al. (2011) presented a method for weed detection based on row identification in videos taken in a maize field. After segmentation using a color index, two methods for row detection were used: a fast method using vertical projection and a slower and robust process that finds persistent vegetation at the same pixel location through a logical AND operation across multiple frames. They reported an average accuracy of 95% for detection of weeds and 80% for the detection of crops when the algorithm was tested with images from varying illumination and field conditions. Vertical projection method for row detection was also used by J.-L. Tang et al. (2016). They used a linear scanning method to find the centerline of the row and calculated a weed infestation rate for image patches. This information was used for a Bayesian decision step that provided a spray/no-spray decision for herbicide application that had an accuracy of 92.5% compared to human decisions. Montalvo et al. (2012) used a row detection method based on least squares linear regression and built binary templates based on the location of the detected row lines. Tenhunen et al. (2019) used a clustering algorithm to detect crop rows in aerial images of a rye field.

The Hough transform is also a commonly used technique for detecting rows in segmented images (Gonzalez-de-Santos et al., 2017; Louargant et al., 2018; Pérez-Ortiz et al., 2015). The detection of crop rows can also be used for navigation of the weeding robot as shown by Gonzalez-de-Santos et al. (2017), where the location of rows was used as correction to a navigation system for a system of ground and aerial robots with a primary navigation system using GNSS.

While the use of spatial distribution information has been successfully used to detect inter-row weeds, contextual information alone is not sufficient. Midtiby, Åstrand, Jørgensen, and Jørgensen (2016) conducted a study to determine the upper limit for the detection of weeds using contextual information alone. They determined that the information about plant position is not sufficient for a detection accuracy higher than 95% when commonly encountered weed infestation rates are considered. They based their conclusion on the assumption that the cost of manual weeding will be lower than the cost of losses incurred at error rates greater than 5%, and concluded that morphological and spectral features must be used for more accurate results.

Spatial, Spectral, and Texture Features

Shape features have been frequently extracted from crop and weed pixels for training of supervised classification models. These are derived from the connected components in the binary images resulting from the segmentation process. The derived features can include geometric properties such as area, perimeter, major or minor axis lengths, eccentricity, and circularity. Bakhshipour and Jafari (2018) extracted these shape factors along with Hu's moment invariant features (Hu, 1962) and Fourier descriptors from segmented images of a sugar beet field. They used these features to train a support vector machine and an artificial neural network and compared the performance of these two models for the classification of sugar beets and four different species of weeds. They found that the support vector machine provided better performance with an overall accuracy of 95% with 93.33% of weeds being correctly classified. Shape features with support vector machines were also successfully used by Kazmi, Garcia-Ruiz, Nielsen, Rasmussen, and Andersen (2015) and Rumpf et al. (2012). Models based on shape features are affected by occlusion, leaf damage, and by the growth of plants, and because of this, shape features are often combined with texture and spectral features.

Golzarian and Frick (2011) extracted a combination of shape, texture, and color features that were reduced to three descriptors using Principal Component Analysis. A discrimination model was created and weed images were differentiated from wheat images with accuracies around 85%. Sujaritha et al. (2017) used texture features with a fuzzy classifier to detect weeds in sugarcane fields with an accuracy of 92.9% at 0.02 s per image. Bawden et al. (2017) used local binary patterns and covariance features to identify weeds in a cotton field through feature matching. They found that classification using covariance features outperformed classification based on local binary patterns; classification accuracy of 92.3% was achieved across multiple weed species. Sabzi, Abbaspour-Gilandeh, and García-Mateos (2018) started with 126 color features and 60 texture features for objects in segmented images of a potato field. They reduced the number of features using a metaheuristic algorithm, and trained a neural network classifier that provided an accuracy of 98.38% at 0.8 s per image. Texture features alone were used with an artificial neural network model to discriminate weeds in a sugar beet field by (Bakhshipour et al., 2017).

Hyperspectral Imaging

As an addition to the spectral information contained in color images, vegetation reflectance information beyond the visible range is commonly used and is a promising tool for the discrimination between weeds and crop species (Slaughter, 2014). Having spectral and spatial information over a range of wavelengths allows for robust segmentation of vegetation as well as for the discrimination based on additional spectral features. For example, Herrmann, Shapira, Kinast, Karnieli, and Bonfil (2013) acquired images using a visible-NIR camera and used partial least squares discriminant analysis for pixel level classification into wheat, broadleaf weed, and grass weed. Using an RGB image acquired in the field for ground truth information, an overall accuracy of 72% was reported. As in the case of RGB imaging, results have been obtained by using a combination of multiple features as opposed to spectral features alone. Lin, Zhang, Huang, Wang, and Chen (2017) conducted a laboratory study using hyperspectral imaging for the discrimination of maize leaves from those of six different species of weed. They found that spectral and shape features were the most important for the classification of species, while texture features were found to be helpful in reducing error rates in classifying among weed species.

The usefulness of hyperspectral imaging comes with the challenge of multi-dimensional datasets and the need for special instrumentation for data collection in the field. While some studies make use of the entire spectral range to train classification models (Yun Zhang, Slaughter, & Staab, 2012), feature selection methods are also used to select the most relevant spectral features and to remove redundant or collinear variables (Wendel & Underwood, 2016; Yanchao Zhang et al., 2019). Most of these studies use line-scanning imagers and thus require a method for precise movement of the imager over the crop rows. The hyperspectral imaging system is usually mounted on a tractor or a ground robot and enclosures with artificial illumination are also used (Yanchao Zhang et al., 2019; Y Zhang & Slaughter, 2011). Snapshot hyperspectral imagers have also been proposed to deal with the challenges associated with the line-scanning systems (Gao, Nuyttens, Lootens, He, & Pieters, 2018).

DEEP LEARNING IN WEED DETECTION

While computer vision approaches have been fairly successful in weed identification, in recent years deep learning models such as Convolutional Neural Networks (CNNs) have emerged as the dominating models in computer vision tasks. Image classification and object detection models based on CNNs have also been proposed for the task of weed discrimination, and successful implementations have been presented in multiple agricultural problems (Kamilaris & Prenafeta-Boldú, 2018). In case of weed detection, the problem becomes a special case of plant species classification.

The advantage in using deep learning models is that they make segmentation and feature selection redundant since the extraction of features and the mapping of learned features to an output result are built into the network. In their study on weed detection in soybean fields, dos Santos Ferreira, Matte Freitas, Gonçalves da Silva, Pistori, and Theophilo Folhes (2017) presented a comparison between a CNN-based image recognition and three other methods using hand-crafted features: SVMs, AdaBoost, and Random Forests. Field images acquired using a UAV were first segmented by a method based on super-pixels and images with the derived super-pixels representing plants were used as input for the CNN model. Shape, color, and texture features were extracted for the feature-based models. Upon comparison, they found that the CNN model provided an accuracy higher than 98% for recognition of soil, soybean, broadleaf, and grass. The feature-based models also provided comparable results, but the authors concluded that the convenience of not having to manually craft input features for the model made the CNN model superior.

CNNs also have the advantage of being able to handle images with occlusion, unlike the classification methods using shape features. Dyrmann, Jørgensen, and Midtiby (2017) used a fully convolutional neural network model for recognition of weed location in cereal fields with high occlusion. They were able to detect 46% of the weeds in the field and make progress in weed discrimination in cereal fields where traditional methods have not been successful. Ma et al. (2019) also made use of a semantic segmentation model SegNet (Badrinarayanan, Kendall, & Cipolla, 2017) based on fully convolutional network and achieved an accuracy of 92.7% in segmenting rice seedlings and weeds. Both of these studies made the use of transfer learning, which is the practice of using pre-trained models for the initialization of CNN filters. Espejo-Garcia, Mylonas, Athanasakos, Fountas, and Vasilakoglou (2020) also used transfer learning methods by exploiting pre-trained CNN models in combination with support vector machines to detect common weeds in cotton and tomato plants with over 99% accuracy. Models trained on large datasets are used in cases of applications where the dataset may be limited, and this has been found to be advantageous even if the pre-trained model was trained on completely different data (Oquab, Bottou, Laptev, & Sivic, 2014).

The requirement for a large amount of training data is one of the challenges associated with using CNN models for detection of weeds. Like all supervised models, the object detection models are only able to perform well on data that comes from the population of data which it has already been trained on. A commonly used technique to mitigate this problem is data augmentation, where transformations such as rotated versions of the available images are used as additional data (dos Santos Ferreira et al., 2017). Olsen et al. (2019) presented a large dataset named DeepWeeds with 17,509 labelled images of eight different species of weeds found in Australian rangelands. To establish a baseline for performance, they used deep learning models Inception-v3 (Szegedy, Vanhoucke, Ioffe, Shlens, & Wojna, 2016) and ResNet-50 (He, Zhang, Ren, & Sun, 2016) to obtain classification accuracies greater than 95%, demonstrating a real-time performance of 53.4 s per image with the ResNet-50 model. Lammie, Olsen, Carrick, and Azghadi (2019) used the DeepWeeds (Olsen et al., 2019) dataset to conduct an experiment using FPGA inference engines for faster and energy-efficient application of deep learning models. This is an especially relevant direction of research since the computational power of mobile devices that can be carried by a weeding robot can be a limitation in terms of both speed and energy consumption. Comparison of two commonly used NVIDIA GPU devices in their performance for weed detection using a deep learning model was also conducted by Partel, Kakarla, and Ampatzidis (2019). A study that used a Raspberry Pi computer to realize real-time application of deep learning models was also conducted by Chechliński, Siemiątkowska, and Majewski (2019). Additionally, Milioto et al. (2018) investigated real-time semantic segmentation of crop and weed images using a CNN model which was fed arrays of vegetation indices as input.

An additional challenge that arises with the large datasets for deep learning algorithms is the necessity to label the images. Labeling of data is also a problem with non-deep learning methods previously discussed and several studies have attempted to create unsupervised detection methods without the need to select or label training data.

Unsupervised Methods

Unsupervised methods for weed detection presented in literature commonly use the regular sowing pattern of crops in rows. The method involves segmentation of vegetation followed by the detection of crop rows, after which the vegetation between the rows is automatically labeled "weed" for training a classification algorithm. Louargant et al. (2018) used this method in multispectral images of a sugar beet field, where the algorithmic labeling was used to train a SVM classification model. Bah, Hafiane, and Canals (2018) used a similar approach for automatic labeling of blobs for training a deep learning model. Pérez-Ortiz et al. (2015) also used this approach in their study on semi-supervised mapping of weeds in a sunflower field using an imaging device mounted on a UAV.

Unsupervised clustering algorithms have also been proposed as alternatives to the supervised techniques (dos Santos Ferreira, Freitas, da Silva, Pistori, & Folhes, 2019; Hall et al., 2017; J. Tang et al., 2017). dos Santos Ferreira et al. (2019) used clustering algorithms based on deep neural networks, and concluded that the best classification accuracy can be obtained when a semi-supervised approach is used. J. Tang et al. (2017) reported that using a k-means feature learning algorithm to initialize parameters for a CNN model increased the accuracy of weed detection. Similarly, Hall et al. (2017) proposed a clustering approach based on deep learning models for enabling weed scouting in unknown fields. A classification method using deep CNN that allowed for reduced labeling due to image clustering was also presented by Hall, Dayoub, Perez, and McCool (2018).

Field Coverage for Robotic Weeding

In addition to weed detection, it is also critical to ensure adequate and efficient coverage within a field for autonomous systems to be effective. For a single autonomous weeding robot, a coverage path must be generated to ensure the system optimally covers the target area. When multiple robots are considered, weeding tasks and the target area must be divided to minimize resources and ensure that no two robots cover the same area. These systems must be coordinated in some way, and have either centralized or decentralized communication, and offline or online task planning, depending upon assumptions and operating conditions. Generating trajectories for groups of cooperative or collaborative robotics for autonomous agricultural operations, namely weed control, presents a challenge due to changing environmental conditions, broken or limited communication links, actuation limitations, and the physical constraints of field crops. However, recent pushes towards developing autonomous agricultural equipment have resulted in numerous path planning and task allocation methods for agbots that attempt to overcome those challenges. This section focuses on task allocation and coverage path planning approaches for autonomous agricultural ground robot systems that consider parameters specific to row cropping systems, instead of generic ground vehicle solutions.

Coverage Planning

Coverage planning is a topic that has a rich history of literature in the robotics community (Galceran & Carreras, 2013; Zafar & Mohanta, 2018). Given an area of interest, the goal of coverage planning is to plan a path which covers the entire target environment considering the vehicle's motion restrictions and sensor characteristics, while avoiding obstacles (Galceran & Carreras, 2013). The task of guiding a ground-based robot through a field to effectively manage weeds can be considered an instance of this coverage problem in which robot motion is restricted to moving parallel to pre-existing crop rows within the field. Additionally, it is important that the generated trajectories are near optimal, given that operator-selected paths may not be most efficient (Zhou, Jensen, Bochtis, & Sørensen, 2015).

Typically, decomposition methods are used prior to applying a solution for coverage planning to separate an irregular shaped area, such as an agricultural field, into subregions called cells, which reduces concavity and simplifies coverage (Choset, 2001). Decomposition methods can be exact, such as the trapezoidal or boustrophedon methods, which break the region into cells that exactly cover the free space within a field taking obstacles into account (Choset, 2000; Choset & Pignon, 1998); or, they can be approximate, in which the cells have a predefined shape and cannot represent the free space exactly (Latombe, 1991). These cells may then be covered by a single robot; for example, Ball et al. (2015) developed a coverage planner that used the boustrophedon decomposition method for coverage planning for N number of robots, where each robot was designated to cover a single cell. They evaluated this coverage planner with one real robot and 12 simulated robots, resulting in 9.7% overlap coverage and only 2.6% missed coverage, which was largely due to obstacle avoidance. To solve the problem of which cell to visit first, Zuo, Zhang, and Qiao (2010) represented the sub-region as nodes of an undirected graph, and a depth-first search algorithm determined the covering order of sub-regions. Their method resulted in an overall reduced number of turns, which can be a difficult maneuver for kinematically constrained ground vehicles in agricultural fields.

In Hameed, Bochtis, and Sørensen (2013), a decomposition method for agricultural fields was developed that could adapt to obstacles of any shape or size, generate headland pass polygons, as well as utilize a user-specified driving angle to capture farmer practices. In addition to cell decomposition, their method also incorporated a genetic algorithm solver to determine the optimal cell sequence for a vehicle to visit. Once a field has been decomposed into regions, an optimized type of fieldwork coverage pattern, called the B-pattern, can be algorithmically computed based on a set of optimization criteria of mobile kinematics and dimensions (D. Bochtis, 2008; D. D. Bochtis, Sørensen, Busato, & Berruto, 2013). A comparison of B-type patterns and traditional (i.e., lawnmower) patterns resulted in a total energy consumption reduction from 3% to 8% in simulation (Rodias et al., 2017).

Many of the above coverage planning approaches assume operation in a 2D plane; however, in reality, many agricultural field settings have hilly or rolling terrains, and incorporating this 3D information into vehicle planners can improve efficiency. Jin and Tang (2011) developed a 3D coverage planning algorithm that considered several 3D costs (headlands, soil erosion, and curved paths) and applied different coverage planning patterns to subregions. This approach reduced both headlands turning cost and soil erosion cost by 10.3% and 24.7%, respectively. Hameed (2014) developed an exhaustive search method to determine the optimal driving angle of an agricultural machine with the lowest energy requirements by generating a 3D representation of the field based on digital elevation models, with an average energy reduction of 6.5% when evaluated on spatial field data. An improved method for identifying optimal driving angles was later developed that considered the change in distance between adjacent paths due to projecting a 2D coverage plan onto a 3D space (Hameed, la Cour-Harbo, & Osen, 2016).

The boustrophedon method and similar exact methods are primarily static in nature, in that they do not allow for modifications in the cell decomposition in real-time. For precision weeding applications, this may present a problem when one or multiple vehicles fail and cannot complete their assigned coverage task. Drenjanac, Tomic, Klausner, and Kühn (2014) developed a space-based decomposition algorithm that supports dynamic portioning to enable assigned areas to change or update during the mission.

Task Allocation and Planning

One of the most challenging aspects of multi-robot systems is how to optimally assign a set of robots to perform tasks such that the overall performance is maximized given a set of constraints. The task allocation problem for automated weeding is allocating 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, where the task planning tasks are distributed between all robots within the system; additionally, there are some hybrid centralized-decentralized approaches. Each of these approaches has benefits and disadvantages, and examples of multi-robot task allocation and planning for weeding robots are described below.

Centralized Planners: The European Project RHEA (Robot Fleets for Highly Effective Agriculture and Forestry Management) project aims to develop a fleet of smaller vehicles for crop management, with a focus on physical weeding. Their proposed system uses a centralized Mission Manager responsible for task planning based on goals and available resources and leaving the option to change the goal in case of system failure (Gonzalez-de-Santos et al., 2017; Gonzalez-de-Santos, Ribeiro, & Fernandez-Quitanilla, 2012). Ball et al. (2015) also used a central multi-robot planner module that communicated perimeter and waypoint data to each robot, but each robot was designed to operate autonomously within its assigned cell. While central planners may be able to more effectively allocate tasks to multiple robotic systems, reliance on connectivity and potential connectivity loss between the planner and individual agents remains a challenge, in addition to the lack of robustness against failure of the planning agent.

Decentralized Planners: Drenjanac et al. (2014) developed a distributed task planner for precision agriculture robot coverage using a space-based middleware. In this approach, robots send local information about location, available resources, and their capabilities as a query to the middleware, after which they received a “matching” task and will continue to execute it. Janani, Alboul, and Penders (2016) developed a real-time task allocation planner only using the local information on each robot without requiring inter-robot communication. In their approach, the number of robots must be equal to the number of regions in the field, and robots claim a region by occupying checkpoints outside of the region. The benefit of this approach is that it does not rely on communication or particular starting points for each robot; however, it requires each robot to find an unoccupied checkpoint which may be inefficient.

A cooperative task assignment strategy was developed by Li, Remeikas, Xu, Jayasuriya, and Ehsani (2015) that obtains information from all “follower” robots and uses a greedy search algorithm to rank possible vehicle formation options. This task assignment can be retrigged by different types of events, such as obstacle detection, robot failure, or task completion, after which a new formation ranking occurs. Vehicle formations for citrus harvesting were evaluated, although new formations for robotic weeding could be developed within this framework.

A coordinated planner (modeled as a foraging task) was developed by McAllister, Osipychev, Davis, and Chowdhary (2019) that maximizes a reward metric, which was set to be the total maximum height of weeds in subsets of the field; this metric was platform-specific as it ensured the weeds did not grow larger than the specific weeding mechanism could control. Their framework was evaluated in a simulation environment based on weed growth models, named Weed World and developed by the authors, which enabled a row-based reward calculation. This information was then used in the optimization algorithm to plan over all robots, sending each robot to a row with a max value, which continued asynchronously after each row was completed (McAllister et al., 2019). This method was able to evaluate different levels of information sharing and robot environmental observability, and more information sharing resulted in higher total reward for the weed planner. These processes are more dynamic than a single-time offline centralizer planner, making them more redundant to failures or changes that might occur during the mission.

Progress on Development of Field-Ready Robotic Weeding Systems

Commercially Available Systems

The agricultural industry has been working over the past decade to build autonomous robots that can perform mechanized weeding, as well as precision spraying. In general, there has been three main considerations for constructing these robots: 1) ease of movement of the robot within an agricultural field, 2) autonomous weed sensing, and 3) selection of an appropriate mechanism to remove the weeds. Arguably, one of the most important areas of ongoing development for commercially available autonomous weed removal robots is highly accurate weed sensing capabilities. Currently, there are three weed sensing systems commercially available: WeedSeeker (Trimble, Sunnyvale, CA, USA), WEED-IT Quadro (WEED-IT, Netherlands), and H-Sensor (Agricon GmbH, Ostrau, Germany). Both the WeedSeeker and WEED-IT technologies differentiate between plants and background material by assessing reflectance. The WeedSeeker incorporates near infrared LEDs, while the WEED-IT Quadro system uses blue LEDs and can operate day and night. The H-sensor is capable of detecting green on green and is designed for weed identification for site-specific weed management strategies. Originally developed with a German weed classification database, the H-sensor is currently being further developed for weed identification in Australian cropping systems.

Several commercially available inter-row cultivation systems used some form of controlled lighting for weed and plant identification. An inter-row guidance system for mechanical weed control (Tillett and Hague Technology Ltd., Bedford, United Kingdom) utilizes a forward-facing camera and digital image template matching to detect crop rows, individual crops, or weeds. The Robovator (F. Poulsen Engineering, Denmark) is a vision-based hoeing machine for controlled mechanical or thermal weeding in row crops that uses artificial lighting for consistent image quality in their camera- based weed detection system. Similarly, the Steketee IC Weeder (Sutton Agricultural Enterprises, Salinas, CA, USA) is an inter-row cultivating machine that uses hooded cameras with high powered LEDs to reduce variation in illumination for identifying plants.

Garford Farm Machinery Ltd. (Peterborough, United Kingdom) developed their Robocrop video image analysis technique to locate individual plants. Their Robocrop InRow Weeder uses this technology in combination with tillage tools to mechanically remove weeds from both between and within crop rows, with a focus on transplanted crops. The Row Crop Thinner by Agmechtronix (Silver City, MN, USA) also uses machine vision to identify plant locations, and although this system eliminates unwanted plants through applying herbicidal spray, the technology could be adapted in the future for mechanical weed removal. Naïo Technologies (Escalquens, France) has developed Dino, an electric autonomous weeding robot, that uses computer vision to guide a variety of tools for weed removal including hoe shares, spiked harrows, or rotary hoes. Their system has been commercially available since 2017.

Systems that are Near-Commercialization

Several start-up companies and academic institutes have developed automated weeding systems that are currently ongoing testing on a limited scale. Blue River Technology (Sunnyvale, CA, USA) is developing a computer vision and machine learning-based weed detection system utilizing a controlled lighting cover. Although it is currently being developed for see-and-spray applications, the weed detection technology could be used for mechanized weed control in the future. Vision Robotics Corporation (San Diego, CA, USA) is developing a vision-based mechanical weeding system that went into field testing early 2018. Ecorobotix is developing a solar-powered, autonomous weeding robot, the AVO, that uses machine learning for weed detection across multiple row crops. Their system is currently being developed for spot spraying, although the Delta manipulation could potentially be used for mechanical weed removal in the future. Deepfield Robotics (Bosch, Gerlingen, Germany) in partnership with Osnabruck University and Amazone (Hasbergen, Germany) have developed BoniRob, a multi-purpose agricultural robot. Their weeding application for this system utilizes a mechanical stamping mechanism and machine learning to identify and kill young weeds at a rate of approximate two weeds per second (Michaels, Haug, & Albert, 2015; Sellmann et al., 2014).

The AgBot II is a prototype for a modular crop and weed management robot currently being developed by researchers at Queensland University of Technology. 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 blade hoe implements, a precision spray system, or a combination of both (Bawden et al., 2017). This system has been tested in preliminary field trials, with plant species detection accuracy greater than 90%. The Ladybird, currently under development at the Australian

Table 1: Summary of robotic systems either commercially available or near-commercialization

Company	System	Weed Detection Approach	Cropping System	Availability
Trimble	WeedSeeker	Reflectance to determine plants vs. background	Row crops	Commercial
WEED-IT	WEED-IT Quadro	Reflectance to determine plants vs. background	Row crops	Commercial
Agricon	H-Sensor	Detects green on-green; currently being developed for species classification	Row crops	Commercial
Tillet & Hague	Inter-Row Guidance	Autonomous mechanical weed control using cultivation tools and cameras	Row crops	Commercial
F. Poulsen Engineering	Robovator	Vision-based hoeing machine for mechanical or thermal weed control	Row crops	Commercial
Sutton Ag. Enterprises	Steketee IC Weeder	Inter-row cultivation machine that uses hooded cameras for identifying weeds	Row crops	Commercial
Garford Farm Machinery	Robocrop InRow Weeder	Uses their Robcrop video analysis tool to locate individual plants for mechanical weed removal	Row crops (transplant focus)	Commercial
Agmechtronix	Row Crop Thinner	Machine vision to identify weed locations for precision spraying, could be adapted for mechanical removal	Row crops	Commercial
Blue River Technology	See & Spray Agriculture Machines	Computer vision and machine learning approach for weed identification; currently for see-and-spray, could be used for mechanical removal	Row crops (cotton focus)	Startup (ongoing testing)
Vision Robotics Corporation	Mechanical Weeder	Vision-based mechanical weeding system	Row crops	Startup (testing began 2018)
Ecorobotix	AVO	Solar-powered see-and-spray weeding; could be adapted for mechanical removal	Row crops	Startup (possibly available fall 2020)
Deepfield Robotics	BoniRob	Mechanical weed stamping mechanism, guided by machine learning for weed identification	Row crops	Startup (ongoing development and testing)
Queensland University of Technology	AgBot II	Computer vision and lighting modules to identify and remove weeds with either mechanical hoe implements and/or precision spray system	Row crops	University research
Australian Centre for Field Robotics	Ladybird	Sensor-based targeted weed removal	Vegetable production	University research
SwarmFarm	SwarmBot	Uses existing optical spray technology with their newly developed small, lightweight machines	Row crops (testing in cotton)	Startup (limited testing)
Naïo Technologies	Dino	Computer vision-based guidance of mechanical tools (hoes, spiked harrows, or rotary hoes)	Vegetable production	Early commercial (since 2017)
Small Robot Company	Dick	Electricity-based weed removal	Row crops (early focus on wheat)	Startup (early trials pending 2020)

Centre for Field Robotics (ACFR), is a ground robot for vegetable production equipped with hyperspectral, thermal, and infrared sensors that can perform a variety of tasks, including targeted weed removal (Underwood et al., 2015). Although their weeding systems currently use existing optical sprayer technology, the company SwarmFarm (Queensland, Australia) is developing smaller, autonomous robots for a wide range of agricultural applications that can more efficiently scale across farms of different sizes. A similar concept is currently being explored by the startup Small Robot Company (Salisbury, England, United Kingdom), which is developing an autonomous, non-herbicide weeding robot Dick that will use electricity (RootWave, Warwick, England, United Kingdom) to kill weeds.

Discussion and Conclusions

Machine Vision for Robotic Weeding

A variety of imaging and machine vision systems have been used with weeding robots for the spatial location of weeds in the field. Most studies use RGB images followed by identification of the weeds in the images. The traditional approach in dealing with RGB images follows from segmentation to feature extraction to supervised modeling. A more detailed description of these methods for ground-based RGB imaging can be found in Wang, Zhang, & Wei, 2019. While segmentation is overwhelmingly conducted using spectral properties – the greenness of vegetation or ratios such as NDVI – multiple approaches have been used in the steps involving feature extraction and modeling. Spatial context is a reliable and popular feature used to separate crop from weeds, at least in the case of modern field agriculture where regular geometrical arrangement of crops can be assumed. Although this is a simple and useful feature to use for visual discrimination of weeds, it is only useful for detecting weeds between rows, and limitations to the sole use of spatial context have been reported (Midtiby, Åstrand, Jørgensen, & Jørgensen, 2016). As a result, shape, spectral, and texture features are usually included in the feature set. Additional features such as 3-D information are sometimes integrated into the process (Gai, Tang, & Steward, 2019). The use of hyperspectral images is more limited in robotic weeding because of the speed of acquisition, instrumentation challenges, and uncontrolled illumination in the field. Studies leveraging the advantage of the spectral information beyond the visible range do exist with creative solutions for instrumentation and lighting.

A more recent development facilitated by the availability of vast computing resources and the ubiquity of digital imaging is the use of deep CNNs for weed detection. One of the advantages in using this method is the elimination of the feature extraction step. The model is trained using labelled images, and the feature extraction and learning are integrated in the model itself. CNN-based models are also useful in situations where weed detection must be conducted in situations other than fields with row-based cultivation, such as in rangelands. Olsen et al., 2019 presented deep learning methods for detecting weeds in the Australian rangeland, and they also provided a labeled dataset from their experiment. Availability of large datasets is a prerequisite for the successful use of deep learning methods, and creation of such datasets will be important for different field environments. One of the concerns with using deep learning models for robotic weeding is the ability to run the detection in real time. Recent studies have shown that rapid in-field detection is possible using deep learning models, without specialized computing resources. Another concern in using deep learning models is the effort required in labeling the large datasets for training deep learning models. Techniques for reducing the labeling effort have been presented, which include classification using contextual information and using the classification result for training the deep learning models. This method is also used to implement unsupervised or quasi-supervised weed detection using RGB or hyperspectral images.

Image acquisition using UAV's has been attempted, with or without coordination with ground robots, and the weed detection methods used are similar to the ones employed in ground-based imaging. Studies to ensure that sufficient resolution is obtained using UAV imaging have also been conducted (Torres-Sánchez, López-Granados, De Castro, & Peña-Barragán, 2013). Velocity of these approaches, however, is limited by the following: i) computer vision and machine learning models that do the detection in real-time, and ii) camera technology and lighting conditions that may result in blurry images (for example, detection limited to 400 mm/s in Michaels, Haug, & Albert, 2015).

Vehicle Coverage and Path Planning for Multi-Vehicle Fleets

While autonomous weed detection is one primary challenge area for robotic weeders, task allocation and field coverage are just as important for designing autonomous weeding systems. Efficient and optimized routes must be developed to ensure appropriate field coverage when multiple robots are used. Due to the fairly structured, and often known *a priori* nature of agricultural fields, established methods for both exact and approximate decomposition have yielded effective results for subsequent coverage planning, but using B-type patterns can reduce energy consumption (Rodias et al., 2017). Many of these approaches, however, made the simplification that planning happens on a 2D plane. In reality, considering the effects of a 3D space affects overall coverage planning, including further reduced overall energy (Hameed, 2014).

In addition to path-planning to ensure adequate coverage, the right robot must be assigned to complete weeding tasks at the right time for optimized, nonredundant operations. There are many approaches to solving this task allocation problem. Centralized planners have been explored for agricultural robotic fleets (Gonzalez-de-Santos et al., 2017); however, due to possible communication barriers in agricultural environments, it is likely that decentralized approaches will be more robust against failure. Some decentralized approaches do not require more information beyond what is available from any given robot (Janani et al., 2016), although some level of information sharing between multiple robots within a fleet will likely improve overall system performance (McAllister et al., 2019). While promising, more in-field testing is necessary to fully evaluate decentralized approaches for agricultural multi-robot systems.

Industry Progress and Considerations for Robotic Weeding Systems

From an industry perspective, there is currently a diverse landscape of commercially available or near-commercially available robotic weeding systems on the market. Many of the currently available systems are autonomous interrow cultivators that use machine vision approaches to detect weeds. These systems tend to be larger machines that can traverse multiple rows in a single pass. While efficient, single machine approaches are less redundant to failures, and their capital acquisition tends to be more costly. On the other hand, there is a recent trend towards the development of smaller, portable, automated weeding robots that can operate alone or in a fleet. These systems offer more flexibility in operation, are redundant against individual system failures, and are more readily transportable between locations if lease models are adopted. Multi-vehicle fleets are also more scalable, because smaller fields may require only one or a few of these systems, while larger fields can scale up in the number of robots in a fleet. Weeding mechanisms that are currently being explored by these systems include electricity, mechanical stampers, and mechanical hoe implements; however, more complex weed removal systems have real-time control challenges (e.g., adjusting position of actuators to uneven ground terrain and vehicle position).

One consideration for future commercialization of portable robotic weeding systems include their development and use as multi-use vehicles. Some vehicles are already being developed with this in mind, for example, the BoniRob system is also being developed with crop scouting abilities. Additionally, for these smaller, portable systems, another consideration that has yet to be addressed is shipping vehicles as either complete vehicles or sent to be put together on site, given the mechanical expertise and capabilities of many farmers in more remote areas who are dependent on fixing their own equipment. Additionally, there is great potential to adapt commercial see and spray technologies that detect weeds on-the-go for mechanical, no-herbicide machines; however, challenges likely remain regarding real time control of mechanical implements and efficiency.

Given the current landscape of innovation and investment into agricultural robots, it is likely that many of these systems will make their way into production farming weed control practices, as weeds remain a significant and persistent problem around the globe. Overall, however, for these systems to be widely adopted, there is room for improvement, and factors like cost, maintenance, and ease of access have to be considered to make these robots commercially feasible at larger scales.

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