BURLEIGH DODDS SERIES IN AGRICULTURAL SCIENCE

Robotics and automation for improving agriculture

Edited by Professor John Billingsley
University of Southern Queensland, Australia

E-CHAPTER FROM THIS BOOK

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SCIENCE PUBLISHING

The use of agricultural robots in weed management and control

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1 Introduction

Weeds are a curse to agricultural production and lead to diminished crop yield and quality. Weed management and control are thus essential to the production of high-yielding and high-quality crops. Advancements in weed control technology have had a huge impact on agricultural productivity. Meeting the food and fiber demands of the world's growing population will only be possible with highly productive agricultural systems in which weed management is a critical component.

Any effective weed control technology needs to be both robust and adaptable. Robust weed control technology will successfully control weeds in spite of variability in the field conditions. Adaptable weed control technology has the capacity to change its strategy in the context of evolving weed populations, genetics, and climatic conditions. Conventional weed control practices, such as chemical weed control or mechanical cultivation, tend to be robust with the input of agricultural producer experience and management decisions. However, they may be less adaptable because they are often applied with large machines, typically large boom sprayers. While these machines have a substantial amount of controller technology to vary several application parameters, the changes are made on a larger scale that is consistent with the size of the sprayers and boom widths.

http://dx.doi.org/10.19103/AS.2019.0056.13

Chapter taken from: Billingsley, J. (ed.), *Robotics and automation for improving agriculture*,
Burleigh Dodds Science Publishing, Cambridge, UK, 2019, (ISBN: 978 1 78676 272 6; www.bdspublishing.com)

Agricultural robots have great potential to deliver weed control technologies that are much more adaptable even down to the plant scale. They potentially could direct chemical or cultivation tools to directly target weed plants. Agricultural robots can have these characteristics because they bring recent advances in artificial intelligence (AI) to bear on the control of weeds in crop fields. However, bringing AI and robotics technology to weed control has several challenges that may limit robotic weed control robustness, at least with the current state of technology.

Weeds are plants that are misplaced or undesirable to the purpose of the crop plants in the field. Crop plants are being cultivated because of the economic value to the producer. Thus, any plant can be a weed, like volunteer corn growing in a soybean field, if it is not serving the purposes of the producer's management scheme. Thus plants are weeds based on their location and competition relative to the crop plants. So robotic weed control is an ill-posed problem until the agricultural producer's intentions for a field are made known to the robot, which will then identify and make decisions about which plants are the weeds that need to be controlled.

Another challenge is that while crop plants are mechanically planted in a structured manner that is compatible with agricultural machinery, weed plants emerge and grow in patterns that are consistent with their ecology. Thus weed plants exist in random patterns in a field. The species of plants that make up the collection of weeds in the field varies. This variability changes at different scales as well. Weed plant emergence changes on a meter-by-meter basis, but also at larger scales: field, farm, county, state, region, and climatic zone.

Weed management strategies take this variability into account and employ weed control techniques that are general and robust enough to be efficacious to control the weeds. In the development of robotic weed control methods, there are obvious challenges to success. These challenges include informing the robot which plants need to be controlled and determining the distinguishing features of those plants. To control weed plants, their growth needs to be retarded or stopped, while not injuring the nearby crop plants. Implementing the control is particularly difficult when the weeds are in close proximity to the crop plants.

The Institute of Electrical and Electronics Engineers (IEEE) provides the following definition for a robot: 'A robot is an autonomous machine capable of sensing its environment, carrying out computations to make decisions, and performing actions in the real world' (IEEE, 2019). Autonomy requires some degree of machine intelligence which involves achieving a particular goal in the context of uncertainty and variability (Jarvis and Grant, 2014; Rzevski, 2003). So while the advances in technology in the area of 'robotic weeding' have been substantial, current automated weeding systems generally lack autonomy so the use of the term robotic is questionable.

Han et al. (2015) developed a multilayer design framework for intelligent machines and field robots consisting of four technology layers (Fig. 1). The layers tend to build on each other, starting with the machine architecture layer which contains both the hardware and software architecture required for the robot's function. Next, the machine awareness layer consists of the perception, localization, and monitoring technology needed for the robot to be aware of its own systems and environment. Robots act upon the world, and thus need to have control systems for the actuators in the machine control layer. For autonomy, being able to achieve goals under uncertainty, the machine planning and supervision technologies associated with the top machine behavior layer are required.

From a review of the literature, technologies that are classified as robotic weeders have typically encompassed technology in the lower three layers such as hardware architecture, perception, and localization and navigation, and implement control. Technologies in the machine behavior layer along with condition monitoring technology are largely absent. Thus it is difficult to say, while in no way intending to diminish the technical work reported in the literature, that we have robotic weeding technology today. However, the developments in the area are progressing rapidly.

Along a similar line of thought, Merfield (2016) compellingly argues that the robotic weeders documented in the literature or commercially developed are not truly robotic weeders, but are 'essentially self-guiding vehicles carrying weeding tools.' His argument is based on the observation that the use of mechanical weeding tools in practice is complex. This complexity is due to several factors such as soil properties varying based on soil type and environmental factors such as soil moisture content, variability in weed plants and crop plants, and the response of these plants to the actions of the mechanical weeding tools.

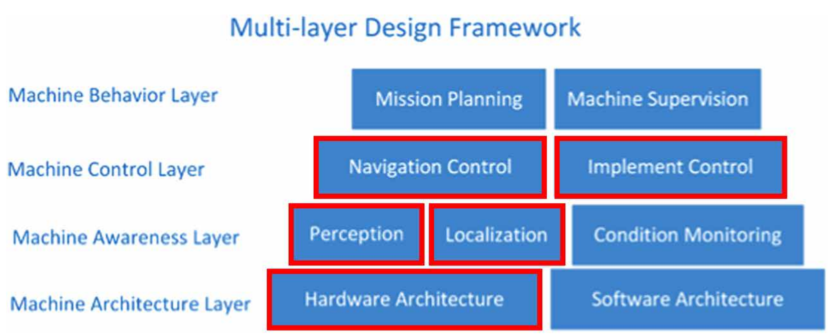

Figure 1 A multilayer design framework for intelligent agricultural machines and field robots. The red boxes indicate technologies that have been typically reported in the robotic weed control literature. Source: adapted from Han et al. (2015).

For agricultural robots to successfully control weeds, several primary challenges must be overcome. First, both crop and weed plants must be accurately perceived in the crop field. The perception system must include plant detection, weed and crop plant classification and plant localization. Secondly, the mechanisms for controlling the weeds must be developed in the context of the weed control strategy that best fits the cultural practices of the production system. Third, based on the information from the perception system, the mechanism must be directed to act at the weed plant locations and away from the crop plants. Fourth, all of these technologies must be integrated together into a weeding system.

This chapter will focus on key work in the development of robotic weeders including weed perception systems and weed control mechanisms. An example of an automated weeding system will be described, and readers will be pointed to where they can learn more.

2 Addressing the challenges of robotic weed control

Much work has been done to address the challenges of robotic weed control. In the subsections below, we will review the literature to provide a perspective on how the challenges have been addressed. The first section will focus on perception systems which can detect and classify weed plants from crop plants. The second section will focus on weed control mechanisms.

2.1 Weed and crop plant perception

After decades of research and development, numerous methods have been developed for weed and crop plant perception. The main challenges in crop and weed plant perception are vegetation detection, classification of weed plants and crop plants, and plant localization. Machine vision is the most widely used technique. Studies vary in terms of crop or weed species, complexity of visual scene (from indoor-controlled environments to commercial fields) and the sensors used. Perception methods can be categorized in terms of the vehicle platforms carrying the sensors, and the plant features used in processing.

Satellite-, aerial- (including unmanned aerial vehicles, UAVs), and ground-based (with unmanned ground vehicles (UGV), such as field robots, or commercially available off-highway vehicles) vehicle platforms are common for detecting and monitoring plants. Satellite- and aerial-based sensing were commonly used for large-scale field monitoring in applications such as variable-rate herbicide spraying (Lan et al., 2010; Torres-Sánchez et al., 2013). These platforms have a lower spatial resolution, and the working time is affected by the weather and air conditions (Moran et al., 1997). Ground vehicle-based sensing and low-altitude aerial-based sensing can acquire higher spatial resolution plant imagery enabling accurate detection of crop rows and plant localization for applications such as real-time, in-row weed control (Hassanein and El-Sheimy, 2018; Li and Tang, 2018). Ground vehicle–based methods, however, must meet requirements such as having clearance over the crop, matching the crop row spacing and being able to traverse the field under a range of soil conditions (Hague et al., 2000).

Spectral reflectance and biological morphology characteristics were two categories of features commonly used in these methods (Slaughter et al., 2008). In the subsections below, weed plant perception methods are reviewed in terms of the type of features used.

2.1.1 Spectral reflectance characteristics

Spectral reflectance characteristics were first investigated, based on the observation that the soils and plants have different spectral reflectance properties (Kyllo, 2003). Soil reflectance is typically low across the visible and near-infrared (NIR) regions with a gradually increasing slope going from visible to NIR and IR regions (Fig. 2). There will be some variations in the reflectance spectrum across soil types. Vegetation reflectance has a very distinctive shape with low reflectance in the visible spectrum, but with increased reflectance in the green region. At the red region, entering into the NIR region, there is a

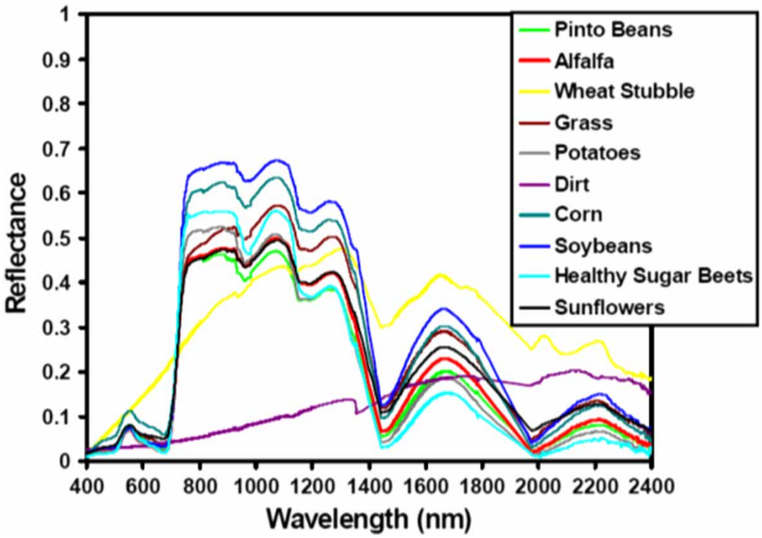

Figure 2 Spectral signatures of different plants and soil. Source: adapted from Kyllo (2003).

dramatic increase in reflectance up into the 50% range. This dramatic increase in plant reflectance is called the red edge and forms the basis for some of the vegetative indices described below.

Starting in the 1970s, spectral reflectance differences between crop, weeds, and soil were explicitly studied (Moran et al., 1997). Algorithms were developed for satellite-, aerial-, and ground-based sensing platforms. Most of the algorithms used images as input signals acquired with cameras that contained charge-coupled device (CCD) or complementary metal-oxide-semiconductor (CMOS) photosensor arrays. Techniques such as machine learning have been used to classify individual pixels into crop, weeds, or soil background categories based on the reflectance intensity values of each pixel. Photosensor arrays are sensitive to visible and NIR light, so by placing light filters on the sensors, light of specific wavelengths can be passed to the sensor. Color cameras, for example, have filters so that the intensity of red, green, and blue light is measured and communicated in different channels. Cameras that measure NIR light are also used as well as combinations of measurements of color and NIR.

Based on the sensor availability, algorithms using visible color reflectance differences were first investigated, using data acquired from color cameras. Various color indices such as the excess green index (ExG) or the hue channel of the hue-saturation-value (HSV) color space were found effective in enhancing vegetation pixels and distinguishing certain species of crop and weeds (Andújar et al., 2012; Foglia and Reina, 2006; Philipp and Rath, 2002; Tang et al., 2000). Since the contrast between plants and soil is strong at NIR wavebands (700–1400 nm), algorithms using NIR were investigated for discriminating plants from soil background. Algorithms using single-channel NIR cameras were developed to segment plants from soil (Brivot and Marchant, 1996; Chang et al., 2004). Additionally, the normalized difference vegetation index (NDVI), which is a function of both NIR and visible color reflectance, was investigated for vegetation pixel segmentation (Gerhards and Christensen, 2003; López-Granados et al., 2006; Torres-Sánchez et al., 2013). Studies were also reported about the use of photodetectors with NIR bands for weed detection in some commercialized selective chemical application systems such as the WeedSeeker (Andújar et al., 2011).

While methods using color and infrared reflectance are reliable for vegetation pixel segmentation, the classification of different plant species was challenging using such a limited number of channels, because of the similarity in light reflectance characteristics shared by most agronomic vegetation (Slaughter et al., 2008). Thus, the reflectance characteristics of a larger quantity of narrower wavebands have been investigated for distinguishing crop and weed plants. Specifically, algorithms using hyperspectral imaging (HSI) were investigated, in which the high data dimension was exploited to achieve higher correct classification rates comparing with only wide color and NIR bands (López-Granados, 2011; López-Granados et al., 2006; Zhang et al., 2012).

In general, one of the greatest potential advantages of the reflectance-based techniques introduced above is the robustness to partial occlusion compared to methods analyzing shapes. Additionally, these methods are normally less computationally intensive than shape-based methods. However, the greatest limitation of the reflectance-based methods is the shortage of reliable information. Reflectance information acquired under imperfectly controlled illumination (affected by the sunlight, especially) is subject to change or may even cause algorithms to fail with many factors, such as weather (e.g. sunny or cloudy) and time (e.g. morning and noon-time). Research is still needed to investigate the stability of classifiers using reflectance information in different field conditions and illumination conditions (Peteinatos et al., 2014). At the same time, introducing plant morphological characteristics has more potential to improve plant classification performance.

2.1.2 Biological morphology characteristics

Another category of weed plant perception methods focuses on biological morphology characteristics, such as the shapes of plant canopy and leaves in the projected two-dimensional (2D) image plane or in three-dimensional (3D) space, to discriminate plants of different species. These methods were mostly designed for applications such as selective spraying and intra-row weeding, in which crop or weeds need to be accurately detected and localized. Ground- and low-altitude aerial-based sensing are two main sensing platforms, on which adequate image spatial resolution can be provided. Techniques such as machine learning are applied to the extracted features to classify species of plants. Since the shapes of plant canopies and leaves are complex and varied, the most challenging task is the investigation of effective and robust descriptors to differentiate different crop species in images.

Historically, most computer vision–based weed perception systems have used light reflectance images as input. Segmentation is usually performed at the beginning to extract vegetation pixels in images. After segmentation, features representing the morphology of plant leaves and plant canopies for plant discrimination are extracted. Common morphological features include length, width, perimeter dimensions, roundness, circularity and convexity of plant leaves or plant canopy. They were reported effective in crop/weed identification (Dyrmann et al., 2018; Tang and Tian, 2008; Wu et al., 2007). General image feature descriptors, such as features from accelerated segment test (FAST), scale-invariant feature transform (SIFT) features, histogram of gradient (HOG), local binary pattern (LBP), and Gabor wavelet transformation, were also found effective in plant detection and discrimination, and robust to illumination variations (Bawden et al., 2017; dos Santos Ferreira et al., 2017; Tang et al., 2003).

However, using light reflectance sensors alone to obtain high discrimination accuracy is challenging unless the light is controlled and the plants are sparse. Since most spectral cameras are passive receivers of reflected light, they are dependent on the quality of the reflected light received. The spectral reflectance similarity of vegetation pixels can lead to difficulties in separating leaves or plants with occlusions, and shadow effects or saturation effects caused by uncontrolled illumination may affect the segmentation and feature extraction performance. There is also loss of structural information because the image scene is projected onto a 2D image plane. Incorrect plant identification results may be obtained using features extracted with such conditions.

3D shape features extracted from 3D point clouds were found promising in addressing some of the problems in plant identification associated with reflectance-based sensors alone. These features are more robust to external illuminance changes and shadow effects than those extracted from color images. Plant height, which is a discriminating parameter between crop and weeds at early crop growth stages, was found effective and beneficial in crop/weed segmentation and classification (Piron et al., 2011).

In the literature, stereovision, light detection and ranging (LiDAR) and time-of-flight (TOF) sensors were three types of sensors commonly used (Weiss et al., 2010). These different sensors have different trade-offs when applied to this perception problem.

Stereovision measures distance between the same real-world point in images acquired in multiple (often two) perspectives. Stereovision is biologically inspired by human binocular vision. To measure the distance between corresponding real-world image points in different images, correspondence algorithms are needed to find corresponding points. Stereovision has advantages of high image resolution, available color information and detailed textural information (Kise et al., 2005), but it is still affected by illumination and has a high computational cost to find correspondences in images (Tippetts et al., 2016). Jin and Tang (2009) demonstrated that 3D structural features extracted from stereovision images were promising in detecting individual corn plants of V2–V3 growth stages and estimating their center locations.

Active range measurement sensors such as semiconductor-based time-of-flight (TOF) and LiDAR sensors measure distance based on the time difference between transmission and reception of modulated light signals. The active sensing mode makes these range sensors more robust under varying outdoor lighting conditions. However, most LiDAR sensors have lower data sampling rates and resolution than TOF cameras, and TOF cameras are more sensitive to sunlight, since infrared light also exists in the ambient sunlight spectrum. In the example of the Deepfield BoniRob robot (Weiss and Biber, 2011), a LiDAR sensor was used to effectively detect and localize outdoor maize plants. Li and Tang (2018) used a TOF camera–based perception system for crop plant detection. 3D features such as point density, curvature, and normal vectors were extracted from the 3D point cloud to detect broccoli and green bean leaves.

Since the morphological features extracted from 2D images and 3D point clouds are complementary, the fusion of color and depth images have been investigated for crop and weed plant discrimination. Common sensors are calibrated color and depth sensor pairs (Herrera et al., 2012), or commercial RGB-D cameras such as Kinect (Microsoft, Redmond, Wash), which directly output registered RGB color and depth images. Algorithms were developed using the fusion of color and depth in different agricultural applications. Kusumam et al. (2017) developed an algorithm to detect mature broccoli heads using an RGB-D sensor for robotic harvesting and obtained a high detection rate. Andújar et al. (2016) employed a Kinect v2 sensor to estimate weed densities in corn fields, in which features such as plant height and canopy volume were used for the classification of crop and weeds. Gai et al. (2019) developed an algorithm to detect broccoli and lettuce crop plants using a Kinect v2 sensor for automated weeding and demonstrated the benefits of fusing color and depth information for plant segmentation.

Compared with algorithms using reflectance features, algorithms based on biological morphology features (especially the shape features) have a higher accuracy in discrimination of plant species with obvious shape differences. These algorithms need data with adequate spatial resolution, and they are more complex than reflectance feature–based algorithms and are thus more computationally intensive. The algorithms are more robust to illuminance changes. The disturbance from sunlight such as shadow effects and image saturation in outdoor applications can be alleviated by providing artificially controlled light sources. But occlusion, leaf damage or other visual 'defects' are the major challenges to algorithms using shape features (Slaughter et al., 2008).

2.2 Weed control mechanisms

While there are many approaches to weed control, most weed control machines typically employ either mechanical or chemical weed control methods. These approaches have been used in conventional mechanized agriculture for many years, and recently, they have been coupled with automation technology to either reduce inputs or exert more precise control of weed plants. While other weed control mechanisms exist, such as flaming, hot water or steam, or high voltage (Blasco et al., 2002), the adoption of these technologies has been low, and little research has been reported to automate them. Thus, this section will focus only on chemical and mechanical weed control mechanisms.

2.2.1 Selective chemical application

Selective spraying systems, sometimes called spot spraying systems, turn nozzles on or off based on what is at nozzle locations. In the case of weed control, once a selective chemical application system perceives the existence of weed plants, herbicide can be applied to the area surrounding the weed locations and not applied in areas where no weed plants exist. This selective chemical application strategy selectively switches nozzles on and off based on presence or absence of weeds and has been investigated for some time in the context of conventional spray application systems. There are some limited examples of commercialized products on conventional spraying platforms such as the WeedSeeker (Trimble, Sunnyvale, California), which uses photodetectors and an active light source to detect vegetation between crop rows. Machine vision–based selective patch spraying has been investigated for row crops that could deliver herbicide onto areas where weeds are present while travelling at typical operational speeds (Tang et al., 2000a; Steward et al., 2002). More recently, selective spraying system are emerging, often in the context of agricultural robotics.

There are also examples of work to increase the spatial resolution of the nozzle with the idea that the spray pattern is intended to be directed to individual plants. Lee et al. (1999), for example, developed and tested a prototype pulsed-jet, micro-dosing actuator capable of applying microliter herbicide dose rates to small target areas as small as 9 mm x 12.7 mm. This small target area was achieved with eight micro-spray nozzles each consisting of five hypodermics each forming a micro-spray nozzle array. Eight micro-spray nozzles were spaced horizontally at a 1.27-cm interval and were located at a 10.16-cm nozzle height (Lee et al., 1999). Similarly, Zhang et al. (2009) reported a system that applied heated oil to weeds using a micro-spray manifold in 6.3 mm by 12.5 mm rectangular areas. This high-spatial-resolution approach to selective chemical application should substantially reduce the volume of applied chemicals to the field over conventional low-resolution nozzles. It may also enable the use of nonselective herbicides to control weeds in the context of high-value vegetable crops.

Other examples of selective spraying include Zaman et al. (2011) who developed a selective sprayer which sensed tall weeds in blueberries using an ultrasonic sensor and selectively applied herbicide to the weeds. Wiedemann et al. (2002) described the development of a selective sprayer designed to control mesquite in road right-of-ways. Infrared light was transmitted horizontally to a receiver. When this beam was interrupted, the sprayer sensed the presence of a mesquite plant and correspondingly applied herbicide to the area nearby and containing the plant. Both of these examples demonstrate the concept of using basic sensing technology to perceive a highly distinguishable feature of weed plants to determine their presence. Additionally, there are examples of selective spraying for other pests (Shen et al., 2017; Zhu et al., 2017).

2.2.2 Robotic selective application

While selective herbicide application systems show tremendous promise in reducing the volume of chemicals applied (e.g. Lee et al., 1999), they by themselves should probably not be considered to be robotic, rather they are automated control systems that respond to perceived weeds in the field. They generally have not included much machine behavior layer technology to deal with uncertain situations. However, more recently, selective spraying technology has been coupled with smaller, automatically guided vehicle technology with hardware and control technology to more precisely apply herbicide. For example, the ecoRobotix spraying robot is autonomously guided through crop rows using GPS and machine vision sensors to follow crop rows. This robot detects weed plants, and then uses two spray nozzles on delta robot arms to position two nozzles over weed plants and selectively apply herbicide directly to detected weed plants (ecoRobotix, 2019; Fennimore and Cutulle, 2019; Fig. 3). The Australian Centre for Field Robotics' Ladybird robot is similar to the ecoRobotix robot, but used a six-axis robot arm (model UR5, Universal Robots, Odense, Denmark) to move a spray nozzle end effector to the weed plants (Bogue, 2016; Fig. 4).

2.2.3 Mechanical weeders

For situations where chemical weed control is not consistent with the producer's management practices, mechanical cultivation or tillage is often used. There is

Figure 3 The ecoRobotix robot senses weeds in the field and then moves spray nozzle to the weed to achieve goal of directly delivering herbicide to each weed plant. Source: ecoRobotix.

Figure 4 Ladybird robot by University of Sydney's Australian Centre for Field Robotics features a novel design covered with solar panels (left) and a selective spraying system in which the spray nozzle is moved close to weed plants by a six-axis robotic arm (right).

a wide variety of mechanical tool designs for mechanical cultivation that can be used with both interrow and intra-row weeds (Bowman, 1997; Bond et al., 2003). Generally, they rely on three main physical techniques for controlling weeds which include burying, cutting, and uprooting the weed plants (Bin Ahmad, 2012). Each of these techniques interferes with the growth of weed plants by killing them or slowing their growth so that the crop plants can overtake the weed plants achieving greater canopy closure and reducing the light interception by the weed plants. Mechanical cultivation is used widely in organic production systems and has been investigated with automated control.

A review of the research and commercial literature found that the majority (75%) of robotic weeders used mechanical over chemical weed control. Of the mechanical types of solutions, there were generally two main classes of approaches: (1) passive cultivation tools being automatically guided through crop rows, and (2) active control of weeding tools in the row and sometimes between the row.

Examples of automatically guided cultivation tools are Naïo Technologies Oz weeder and Dino robot (Naïo Technologies, 2019a,b). The Oz weeder is electrically powered with four electric motors, one in each wheel. It comes in a small package that is 60 cm high and 40 cm wide, weighing 110 kg. Because of its size, it fits between rows of vegetable crops and carries a variety of cultivation tools including several types of harrows or brush or spring weeders for intra-row weeding. The Dino weeding robot (Naïo Technologies, 2019b) is a larger platform with a 130 cm height and adjustable wheelbase from 140 to 180 cm. It is able to span 120 cm of row width, and guides different passive cultivation tools through multiple rows. The Kongskilde Robotti has a similar platform spanning multiple rows and is automatically guided to cultivate the crop rows that it spans (Bawden et al., 2014).

The systems that apply active control of mechanical tillage tools are typically using local scene information from the perception system to actively move the tools into and out of the crop row depending on where crop plants are located. Following this basic strategy, different systems have taken different approaches largely based on their mechanism design.

One common approach is to use a horizontal knife or blade hoe tool that is positioned shallowly below the soil. The blade is moved into the crop row in the spaces between the crop plants cutting and burying weed plants. An early implementation of this strategy was the Sarl Radis weeder developed in France (Van Der Weide et al., 2008; Cloutier et al., 2007). This automated weeder detected reflected light from the crop plants, and accordingly moved the hoes out of the row when a crop plant was detected. Originally developed for transplanted crops, it had highest performance when the weeds were substantially smaller than the crop plants. Similar realizations of this concept include the Robovator, Frank Poulsen Engineering ApS., Denmark; IC-Weeder, Steketee, the Netherlands; and Removeed, Costruzioni Meccaniche Ferrari, Italy (Peruzzi et al., 2017).

Another approach to intra-row weeding is to use a rotating mechanism that is moved in and out of the crop row. Astrand and Baerveldt (2002) used a vertically oriented tool described as 'a rotating wheel that is rotated perpendicular to the row line.' The wheel was raised and lowered pneumatically in the presence and absence of crop plants. Gobor (2013) investigated the kinematics of a similarly oriented hoe mechanism that consisted of 'duck foot' hoes. The distance from the axis of rotation out to the hoes could be varied as well as the rotational speed of the system for flexibility in moving and positioning the tools below the surface near each crop plant. A prototype mechanism was tested under laboratory conditions in a soil bin, and the distance between the crop plant and the disturbed soil was measured. The location of disturbed soil was greater than 25 mm from the crop plants and typically less than 70 mm.

O'Dogherty et al. (2007) investigated the kinematics of a horizontally oriented disk that was pulled shallowly under the soil for intra-row weeding. The circular disk had a 130° section or notch removed from it. In the presence of a crop plant, the disk was rotated so that the notch was positioned to the location of the crop plant leaving it undisturbed while the soil between plants was disturbed. Field trials of the disk tillage tool with a computer vision system for crop plant detection found that crop damage levels were low and the system reduced intra-row weeds in transplanted cabbage (Tillett et al., 2008). This technology was commercialized under the trade name Robocrop (Garford Farm Machinery Ltd, England; Fig. 5).

There are other examples of novel intra-row weeding tools. A cycloid hoe concept was developed and reported on by Nørremark et al. (2008, 2012). The cycloid hoe consisted of eight tines that rotated around a vertical axis (Fig. 6). The hoe mechanism was designed so that individual tines could go into the row in the absence of a crop plant or be retracted when a crop plant was present.

Figure 5 Robocrop automated mechanical weeding system (left) that uses a disk weeding tool for intra-row weeding. The disk is rotated so that the notch in the disk goes around crop plants (right; Source: Tillett and Hague Technology Ltd).

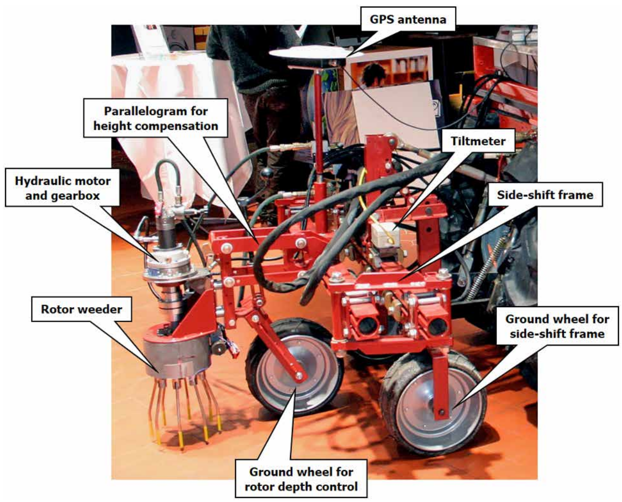

Figure 6 Cycloid hoe mechanical weeding mechanism in which the tines are directly on paths that avoid crop plants when doing intra-row weeding. Source: adapted from Griepentrog et al. (2006).

The system was tested with artificial plants and georeferenced crop plants and was found to be reliable in performing intra-row weeding without interfering with the crop plants. As an example of another mechanism, Langsenkamp (2014) described the development of a weed stamping tool. To injure weed plants, the tool is inserted 47 mm into the soil while centered on individual weed plants. The stamping tool was mounted on a delta robot arm that positioned the tool over detected weed plants. In field tests, 85% of the plants that were stamped died. Johari Jiken (2016) investigated the effectiveness of a rotating tine mechanism in disturbing simulated weed plants with tine depth and rotation speed as experimental factors.

These many clever approaches to mechanically control weeds in and between the crop rows represent substantial technical advances to this problem. Clearly a combination of crop and/or weed plant recognition, actuator control and automatic vehicle guidance are needed for a weeding robot (Slaughter et al., 2008). However, to obtain the autonomy expected by an automated weeding system that is considered robotic, higher levels of machine behavior decision-making is required, such as selection of weeding tool for the combination of crop, weeds, soil type, and soil condition (Merfield, 2016). In addition, mechanical weeding requires operator knowledge to make adjustments to the cultivation tool (Bond et al., 2003), so for a robot to be autonomous, it would need to also make cultivation tool adjustments. Additionally, weeding robots need to make decisions relative to weed control efficacy, but there is a gap here as the efficacy studies associated with weeding robots tend to be fairly limited.

3 Case study

Gai et al. (2019) described the development of a robotic weeder using a new weeding actuator design for mechanical weeding for row crops and multiple crop species. The actuator was designed to be used as a tractor implement mounted on a toolbar, but it could be integrated into a field robot as well. The weeder employs rotating vertical tines as the weeding tool for cutting, uprooting and burying weeds (Fig. 7). Each rotating tine group is positioned relative to the crop row using closed-loop control of servo-motor-driven pivoting arms. The rotating tines move in and out of the crop row based on the presence or absence of crop plants. The perception system employed an RGB-D sensor (Kinect v2, Microsoft, Redmond, Wash) to detect and localize crop plants using color and shape features in real time. After detecting and

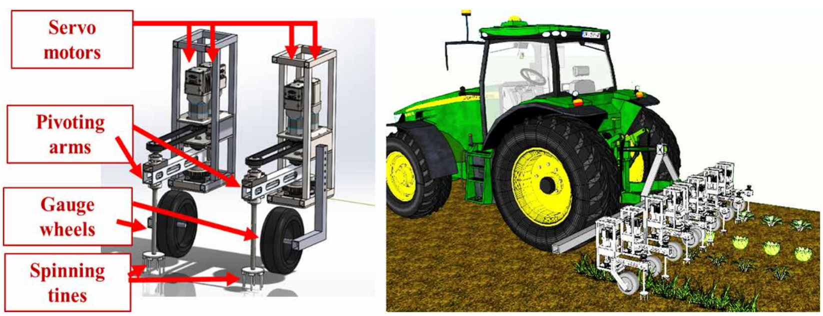

Figure 7 The actuators (left) were designed to be used as a tractor implement (right), employing rotating vertical tines as the weeding tool for effectively cutting, uprooting and burying weeds. Source: adapted from Gai et al. (2019).

localizing crop plants, the tines were controlled to move close to the crop row to remove weed plants regardless of their species while avoiding crop plant disturbance and damage.

The perception system of this weeder used data from both color and range sensors and fused these data together for a high-performing crop plant perception system. The image processing pipeline consists of six steps including data preprocessing, vegetation pixel segmentation, plant extraction, feature extraction, feature-based localization refinement and crop plant classification (Fig. 8). In the preprocessing step, invalid pixels and noise pixels in point clouds were removed. In the segmentation step, the soil surface was modeled as a plane in the 3D point cloud and pixels above the plane were treated as outliers and as crop pixels. In the plant extraction step, plant pixels were clustered based on their spatial relationships to one another. In the feature extraction step, a set of reflectance and shape features for describing individual leaves and plant canopies was extracted. In localization refinement, venation features were used to calculate plant center positions. And in the classification step, the extracted features were used to perform crop-versus-weed classification for each extracted plant.

The mechanical weeders were controlled to follow trajectories based on the perceived location of the crop plant trajectories of the rotating tine units. Trajectories were planned which enabled cultivation as close to the crop plants as possible, without coming into contact with or disturbing the plants.

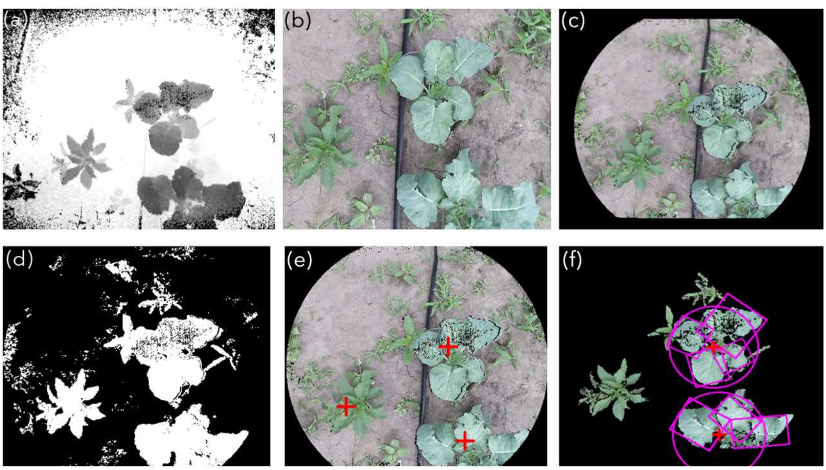

Figure 8 Sample broccoli plant images (16 DAT; 40k lux) at each image processing step including (a) depth and (b) color images; (c) color registration and filtered image; (d) segmented image, with white vegetation pixels; (e) detected plants marked with crosses; and (f) feature-based localization refinement and classification with target crop plants labeled with crosses. Source: adapted from Gai et al. (2019).

Because the interactions between the soil, crop plants, and tine mechanism are so important, a series of experiments were conducted in an indoor soil bin to better understand these interactions. Additionally, the weeding performance of the rotating vertical tine mechanism was studied using small wooden cylinders as simulated weed plants (Johari Jiken, 2016; Kshetri et al., 2019). These cylinders were inserted into the soil, then after the tine mechanism passed by, the location and orientation of each cylinder was observed. Potential weeding rate was analyzed for the rotating tine mechanism at different working soil depths and rotational speeds. Both depth and rotational speed had a significant effect on the potential weeding rate for the mechanism which was found to increase for higher levels of these parameters. Although the width of soil disturbance due to a cylindrical tine is affected by tine diameter and working soil depth, operating parameters such as increased longitudinal and rotational speeds have potential to damage a higher proportion of weed plants.

4 Summary

The work documented in the area of robotic weed management and control demonstrates the potential of automated weeding technology to substantially reduce inputs by treating fields on a much-reduced scale than conventional agriculture, that is, down to a plant or row scale. The following observations can be made about the current state of the art.

- Much work has been directed to the weed/crop plant perception problem. This perception problem has been particularly challenging given the semi-controlled nature of agricultural fields. Variability in lighting, density and species of weed plants, and occlusion of mixtures of plants are some of the main challenges associated with perception systems. Much progress has been reported using combinations of sensors and newer AI approaches.
- A variety of robotic weed control mechanisms have been explored for both chemical and mechanical weed control approaches. In many cases, mechanical weeders show potential to be efficacious under some conditions, but weed control performance studies have been limited.
- Examples of weeders that have machinery behavior technologies included in them are limited. Current robotic weeder examples are limited in being able to achieve goals in the context of variation and uncertainty. For example, there are no reported examples of robotic weeders being able to change tools or adjust tool control due to changing soil conditions.

While these limitations exist, the current rapid development rate of robotics technology will undoubtedly have an impact on the development of robotic weeding technology.

5 Future trends in research

5.1 Future trends in weed perception research

Given the advantages and limitations of the current state of technology for automated or robotic weeding, future research in perception systems will likely focus on either increasing data dimensions or increasing the complexity of algorithms for better weed perception performance. Data dimensions can be increased by fusing sensors from different perspectives or with different sensors that provide complementary information (Barrero and Perdomo, 2018; Gao et al., 2018; Shchez and Marchant, 2000). More complex image processing algorithm can be achieved using deep learning (DL) techniques.

From recent investigations, DL or convolutional neural networks (CNN) is an AI technology that shows promise in agricultural applications. DL uses complex image processing neural networks trained with large amounts of data. Kalimaris and Prenafeta-Boldú (2018) surveyed the literature for research using DL in agriculture and found 40 articles documenting research in this area. All but two of the papers were published during or after 2015. Seven papers focused on weed plant detection (Dyrmann et al., 2016a,b, 2017; Sørensen et al., 2017; McCool et al., 2017; Milioto et al., 2017; Potena et al., 2016).

Compared with traditional pattern recognition methods, higher performance has been reported for CNN methods in crop/weed discrimination and detection. A big advantage of DL is a reduced need to do manual 'feature engineering' to determine the distinguishing features of the plants which allow them to be assigned to the correct class. Because of the complexity of DL models, the technology is able to do feature learning and find distinguishing features in a problem. This capability to learn the plant features which can be used to distinguish crop plants from weed plants could open up the way for substantial advances in the weed perception area. CNN models such as Inception-v3 (Szegedy et al., 2015), GoogLeNet (Szegedy et al., 2014), DenseNet (Huang et al., 2017) and customized models were shown to be effective in crop/weed detection even with uncontrolled illumination and visual defects (Dyrmann et al., 2016a, 2017; McCool et al., 2017; Milioto et al., 2017; Potena et al., 2016).

However, there are some challenges associated with DL. First, DL requires high computational capacity for training and real-time inference. Second, the performance is highly dependent on the quality of the training set. The data set needs to be large enough, and correctly annotated, which usually requires substantial manual labor to collect and annotate images. To improve robustness, the data set must span all conditions such as inconsistent illumination, shadow and occlusion (Kamilaris and Prenafeta-Boldú, 2018). Thus, traditional pattern recognition pipelines are still worth investigation for applications for which it is impractical to have high computational capacity and large data sets. Nevertheless, DL should be a fertile ground for research in the near future.

In the area of weed control mechanism, there is much work to be done. As Merfield (2016) points out, there is a big need for research to investigate the interaction between weeding tools and the soil-weed-crop matrix. More knowledge in this area will enable weeding robots to have a higher degree of intelligence to the point where they can make decisions about the type of tools needed for specific applications or can adjust their strategy based on field conditions at any one point. While Merfield was commenting particularly on a mechanical weed control solution, similar comments and consideration should also be made about chemical weed control as the robotic solutions facilitate new possibilities for reducing application volumes. In all of this, enabling robots and their managers to make decisions in the face of uncertain field environments is wide open for future research.

6 Where to look for further information

More information on robotic weed management and control can be found in journals containing many of the papers cited in this chapter. These journals are often at the interface of engineering and weed science. Examples of such journals include *Transactions of the ASABE*, *Biosystems Engineering*, *Computers and Electronics in Agriculture*, *Precision Agriculture*, and *Weed Research*. The *Journal of Field Robotics* is not exclusively devoted to agricultural robots, but includes agricultural applications and contains many articles about crop plant and weed plant perception. *IEEE* journals, while extremely broad in their technical coverage, also have many technical conference papers on weed detection and classification-related topics. In terms of books, Young and Pierce edited the book *Automation: The Future of Weed Control in Cropping Systems* (2013), which is a good source of information on robotic weeding. This source was written for both the biologist and the engineer and seeks to inform both for solutions needed at this interdisciplinary crossroad. Similarly, Oerke et al. (2010) provides a comprehensive perspective on precision crop protection in the context of heterogeneous crop environments. While it has a broader view than just weed control, this volume does provide much information on weed control systems including those that are used for robotic applications.

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