Weed Technology 2016 30:823–837

Technology for Automation of Weed Control in Specialty Crops

Steven A. Fennimore, David C. Slaughter, Mark C. Siemens, Ramon G. Leon, and Mazin N. Saber*

Specialty crops, like flowers, herbs, and vegetables, generally do not have an adequate spectrum of herbicide chemistries to control weeds and have been dependent on hand weeding to achieve commercially acceptable weed control. However, labor shortages have led to higher costs for hand weeding. There is a need to develop labor-saving technologies for weed control in specialty crops if production costs are to be contained. Machine vision technology, together with data processors, have been developed to enable commercial machines to recognize crop row patterns and control automated devices that perform tasks such as removal of intrarow weeds, as well as to thin crops to desired stands. The commercial machine vision systems depend upon a size difference between the crops and weeds and/or the regular crop row pattern to enable the system to recognize crop plants and control surrounding weeds. However, where weeds are large or the weed population is very dense, then current machine vision systems cannot effectively differentiate weeds from crops. Commercially available automated weeders and thinners today depend upon cultivators or directed sprayers to control weeds. Weed control actuators on future models may use abrasion with sand blown in an air stream or heating with flaming devices to kill weeds. Future weed control strategies will likely require adaptation of the crops to automated weed removal equipment. One example would be changes in crop row patterns and spacing to facilitate cultivation in two directions. Chemical company consolidation continues to reduce the number of companies searching for new herbicides; increasing costs to develop new herbicides and price competition from existing products suggest that the downward trend in new herbicide development will continue. In contrast, automated weed removal equipment continues to improve and become more effective.

Key words: Automation, integrated weed management, intelligent cultivator, intrarow weed control, mechanization, robotic weeding, vegetable crops

Los cultivos hortícolas de alto valor tales como flores, hierbas, y vegetales generalmente no tienen un espectro adecuado de químicos herbicidas para el control de malezas y han sido dependientes de la deshierba manual para alcanzar un control de malezas comercialmente aceptable. Sin embargo, la escasez de mano de obra ha provocado el incremento en los costos de la deshierba manual. Si se pretende contener los costos de producción, existe una necesidad de desarrollar tecnologías alternativas a la mano de obra para el control de malezas en cultivos hortícolas de alto valor. La tecnología de máquinas de visión, combinada con procesadores de datos, ha sido desarrollada para hacer posible que máquinas comerciales puedan reconocer los patrones de siembra en hileras del cultivo y a la vez controlar equipos automatizados que pueden desempeñar labores tales como la remoción de malezas en la hilera de siembra, o ralear la densidad de siembra del cultivo. Los sistemas de máquinas de visión comerciales dependen de la diferencia entre el tamaño del cultivo y el de las malezas y/o de la regularidad del patrón de distribución del cultivo para que el sistema pueda reconocer las plantas del cultivo y las malezas a su alrededor. Sin embargo, donde las malezas son grandes o la población de malezas es muy densa, los sistemas de máquinas de visión actuales no pueden diferenciar efectivamente entre las malezas y los cultivos. Los equipos automatizados de deshierba disponibles comercialmente hoy en día dependen de cultivadores o aspersores dirigidos para controlar malezas. Los equipos de acción para el control de malezas en modelos futuros podrían usar abrasión con aspersión de arena con aire a presión o calor con equipos con llamas de fuego para matar las malezas. Las estrategias de control de malezas en el futuro probablemente requerirán la adaptación de los cultivos al equipo automatizado de remoción de malezas. Un ejemplo de esto sería el cambio de patrones de siembra y distancias entre hileras del cultivo para facilitar la labranza en dos direcciones. La consolidación de compañías químicas continúa reduciendo el número de compañías que están buscando nuevos herbicidas. Además, el incremento en los costos de desarrollar nuevos herbicidas y el precio de la competencia a partir de productos existentes sugiere que la tendencia decreciente en el desarrollo de nuevos herbicidas continuará. En contraste, equipos automatizados de remoción de malezas continúan mejorando y haciéndose más efectivos.

DOI: 10.1614/WT-D-16-00070.1

* Extension Specialist, Department of Plant Sciences, University of California, Davis, Salinas, CA 93905; Professor, Department of Biological and Agricultural Engineering, University of California, Davis, Davis, CA 95616; Associate Professor, Department of Agricultural and Biosystems Engineering, University of Arizona, Tucson, AZ 85721; Assistant Professor, West Florida Research and Education Center and Agronomy Department, University of Florida, Jay, FL 32565; Postdoctoral Research Associate, University of Arizona, Yuma Agricultural Center, AZ 85364. Corresponding author's E-mail: safennimore@ucdavis.edu

Automated weed control technology is available commercially and is being used in vegetable crops like broccoli (*Brassica oleracea* L.) and lettuce (*Lactuca sativa* L.) (Lati et al. 2016). Because of the limited availability of effective herbicides, and high labor used in the production of specialty crops (flower, fruit, herb, vegetable, and other horticultural crops), these crops are most likely to benefit from weed control automation due to reduced labor inputs required for hand weeding (U.S. Department of Agriculture [USDA] 2016). As a group, the highly varied plant architectures and production systems of flower, fruit, herb, vegetable, and other horticultural crops make it challenging if not impractical to develop a one-size-fits-all automatic weeding machine for specialty crops. Weed removal technology developed in specialty crops may prove useful for application in major crops, albeit with required modification for canopy coverage, planting density, as well as operation speed and cost per hectare. Within the last decade, new technologies for crop thinning and weed removal have been developed and commercialized for specialty crops, and there will likely be many more future advances in machine learning and development of smart machines for agriculture.

Herbicides have greatly reduced agricultural production costs as well as contributed toward increasing crop yields (Gianessi and Reigner 2007). A major stimulus for introduction of herbicides was the loss of farm labor for hand weeding and increasing farm labor costs during the 1940s and 1950s. This led to the weed management revolution based on conventional herbicides during the 1960s and 1970s, followed by the introduction of glyphosate-resistant crops during the 1990s and early 2000s (Duke 2012; Shaner 2000). Not all crops participated equally in the dramatic increases in efficiency that conventional herbicides and glyphosate-resistant crops brought to the market. Specialty crops, especially flower, berry, and vegetable crops, do not have an adequate spectrum of herbicide chemistries to provide commercially acceptable weed control by themselves; therefore, hand weeding is also needed to protect many specialty crops (Fennimore and Doohan 2008). Hand weeding, cultivation, and cultural methods of weed management are especially important in organic crops where organic-compliant herbicides are expensive and seldom used in commercial agriculture (Boyd et al. 2006). Because of stricter immigration policies and competition for laborers from nonagricultural sectors, the United States is again finding that farm labor supply does not meet demand, and there is a need for alternatives to hand weeding (Taylor et al. 2012). Rapid industrialization in Mexico with accompanying employment opportunities and farm labor demands in that country have resulted in less farm labor available in the United States. This paper will explore possible alternatives using automation technology to improve weed control systems in specialty crops.

Commercial development of new herbicide active ingredients has greatly slowed in the past decade. As recently as the 1970s and 1980s, several new active ingredients were introduced annually (Duke 2012). Currently, new herbicide active ingredients may cost \$240 to \$300 million from discovery to launch (Castello et al. 2015; Duke 2012; Kraehmer et al. 2014; Lamberth et al. 2013; Rüegg et al. 2007). High development costs will likely limit the number of new herbicide active ingredients in the pipeline, particularly for specialty crops where the number of hectares is low compared to agronomic crops. During the period 1970 to 1991, 15 new herbicide modes-of-action were introduced in Europe, but none after 1991 (Rüegg et al. 2007). During the period 1980 to 2009, 137 new herbicides were introduced worldwide (Duke 2012; Kraehmer et al. 2014). However, in the period 2010 to 2014 only four new herbicides were introduced (Jeschke 2016). Perhaps the increasing difficulties in managing weeds resistant to glyphosate and other herbicides will stimulate some of the agricultural chemical companies to reinvigorate their development efforts (Duke 2012; Shaner 2000). However, the much higher development costs for new chemistries and the fact that there are fewer major agricultural chemical companies today looking for new herbicide chemistry, suggests the downward trend of new herbicide introductions will continue (Duke 2012). Also contributing to the lack of new herbicide chemistry is the availability of established herbicides already on the market and the intense competition among agricultural chemical companies for market share, which holds down prices and must be considered before making a decision to invest in new products (Rüegg et al. 2007).

Automatic weed removal technology provides an alternative path to weed control with reduced

https://doi.org/10.1614/WT-D-16-00070.1 Published online by Cambridge University Press

dependence on both the agricultural chemical industry and hand weeding. Recently, a growing number of new European and U.S. companies with expertise in machine vision, automation, mechatronics (control systems and actuators), and robotics have formed to address labor shortages in the specialty crop industry. The likelihood that this trend will continue is high, as the development of automatic weed removal equipment can be much less expensive than herbicides. For example, the development costs for Steketee's intelligent cultivator (IC) in The Netherlands, was approximately \$11 to \$17 million (Leonard Mol, Steketee, personal communication) which compares favorably to the > \$250 million required to develop a new herbicide (Rüegg et al. 2007). New technologies that combine sensors and mechatronics with existing weed removal technology like cultivation knives and sprayers to create new tools to remove weeds will be discussed.

Automation of weed control has two key aspects, crop/weed detection and weed control actuators. Automatic detection involves machine recognition of key features of the plant and differentiation between the crop and weed. Actuation takes two approaches to weed automation; one approach is chemical and the other mechanical (De Baerdemaeker 2014). Here we will explore examples of both of these approaches with automated lettuce thinners used as an example of automated chemical application and robotic intrarow cultivation as an example of mechanical weed control automation.

Weed and Crop Detection

GPS Guidance. Because of the small size of the crop at the optimum time in the plant life cycle for weed control (Lanini and LeStrange 1991) precise lateral guidance of the sensors and actuators is a critical prerequisite for robust performance in automated weed control systems, particularly those based upon spray targeting of individual weeds (Lamm et al. 2002). The most commonly used technology for precise lateral guidance in specialty crops is currently the real-time kinematic (RTK) global positioning systems (GPS) technology for autoguidance of the tractor. Most modern RTK-GPS guidance systems are compatible with global navigation satellite systems from multiple countries to increase the total number of satellites available and improve reliability. The U.S. Geological Survey (USGS) reports that the accuracy of RTK-GPS location measurement is 3 cm when determined in relationship to a specific geodetic datum (USGS 2016). The second type of technology in use for lateral guidance of automated weed control systems is based on machine-vision crop row following (Fennimore et al. 2010). Under low to moderate weed infestation levels, machine vision guidance systems can outperform RTK-GPS guidance systems because they are more accurate (Slaughter et al. 1999) and because they are typically set up to control the lateral positioning of the cultivation system directly, rather than indirectly through control of the tractor. At high weed infestation levels machine-vision guidance systems can become unreliable. The convenience of having one guidance system for all farming operations (e.g., tillage, planting, harvesting) and the independence of the performance of RTK-GPS from the weed densities/size means RTK-GPS guidance system will likely become the predominant technology for precise lateral guidance of automated weed control platforms.

Once the lateral position of the robotic system has been established, the next task is to identify individual plants within the crop row. The two weed control mechanisms (hoeing vs. spray) led to different requirements of the sensing approach to plant identification. For robotic hoeing, the sensing need is for accurate detection and localization of the crop plants' centroids (center of plant symmetry), and weed detection is not generally needed. For robotic weed spraying, assuming a nonselective phytotoxic solution precisely sprayed on the target weed avoiding the crop and soil, the sensing need is for an accurate map of the location of the weed foliage and here, mapping the crop foliage can be important for minimizing accidental targeting of the crop. Of the two cases, detecting and mapping the crop plants' centroids is the least challenging and has the greatest number of sensing modalities available.

Three general noncontact sensing approaches to automatic detection and mapping of the crop plants' centroids have been demonstrated. The first sensing modality requires a systems approach to crop mapping and the use of RTK-GPS both at planting and during weed control. This concept was developed by Upadhyaya et al. (2003, 2005) and

https://doi.org/10.1614/WT-D-16-00070.1 Published online by Cambridge University Press

has been experimentally verified by Ehsani et al. (2004), Nørremark et al. (2007, 2008), Sun et al. (2010), and Pérez-Ruiz et al. (2012a,b). In this method, an RTK-GPS crop plant map of the seed location, or transplant location is automatically made at planting. The RTK-GPS crop location map is later used by the robotic weed control system to control the position of the robotic hoes automatically, pulling the hoes away from the close-to-crop zone when approaching a crop location in the map, and then back into the row center to control intrarow weeds between crop plants. This sensing approach has the advantages of not requiring any crop- or weed-specific knowledge, is less computationally intensive than machine-vision techniques, has no optical elements that require protection, and does not require any illumination source or control, but requires a GPS-mapping planter or transplanter and the availability of a high-quality RTK-GPS signal both at planting and during weeding events. Recent advances in RTK-GPS technology have greatly reduced the component cost of RTK-GPS equipment, suggesting that this technique may become cost-competitive with other technologies in the near future.

Electromagnetic Absorbance. The second sensing modality that has been demonstrated is the use of X-ray or gamma ray sensing technology for detection of crop plants. The concept was originally developed for lettuce harvesting using X-ray by Lenker and Adrian (1971) and gamma ray by Garrett and Talley (1969) and has been experimentally verified for tomato (*Solanum lycopersicum* L.) plant detection in the field for weed control applications by Haff et al. (2011). The method is based upon the absorbance of electromagnetic energy and requires that the main stem in a central leader crop architecture or central portion in a rosette architecture crop plant have greater absorbance than the weeds, typically by the crop being physically larger. As such, the sensing method is most appropriate for weed control in a transplanted crop, where the crop plants are older and typically larger than the emerging weeds. Like the GPS method described above, it is also used to control the position of robotic weeding hoes into and out of the close-to-crop zone. It is the least computationally intensive noncontact method of crop detection that has been demonstrated in specialty crops. Because it utilizes a penetrating source of electromagnetic radiation (unlike visible or near-infrared light-based methods), it is robust to the visual occlusion of the crop plant center by either crop or weed foliage, an advantage over machine vision techniques. The primary disadvantage is the need to protect workers from accidental exposure to the X-ray or gamma ray source.

Machine Vision Detection. The third, and most predominant sensing modality used in automatic weed control are machine vision techniques. The most powerful, and to date the only method capable of robust, automated in-field discrimination of individual plant species, is based upon hyperspectral imaging. The hyperspectral imaging concept has been demonstrated in the field in lettuce (Slaughter et al. 2008) and tomato (Zhang and Slaughter 2011; Zhang et al. 2012a,b), with between-species pixel-level recognition rates above 75% and crop vs. weed discrimination rates above 90%. The technique uses machine learning to establish a spectral pattern recognition classifier and when used as a proximal sensor (as opposed to remote sensing via aerial vehicles) with both controlled illumination and a thermally stabilized camera, can distinguish between closely related species such as tomato and black nightshade (*Solanum nigrum* L.). Other advantages beyond species identification capability are that it is less computationally intensive than shape-based pattern recognition, it is robust to visual occlusion of the leaf margin (another advantage over leaf shape recognition), and the species recognition ability can be used to customize the spray application of multiple herbicidal materials based upon weed species. Its disadvantages are that it requires a multiseason calibration process (Zhang et al. 2012a,b) and must be trained to distinguish between closely related species. The current cost of hyperspectral imaging camera technology is much higher than traditional digital color imaging hardware; however, recent developments in multispectral cameras for the rapidly growing aerial remote sensing market suggest that lower-cost multiwaveband cameras may be available in the near future.

The most widely studied and only commercially utilized method of sensing in existing robotic weed control machines is based upon traditional 2D machine vision techniques. Although a number of advanced machine vision recognition techniques for plants have been documented in the literature (e.g., Hearn 2009; Manh et al. 2001; Persson and Åstrand 2008; Søgaard 2005), their high level of computational intensity and the predominant use of serial processors in existing robotic weed control machines limits their adoption. More commonly, 2D image processing approaches, based upon a combination of plant detection (from soil) by color or infrared to red light reflectance ratios, and crop recognition (from weeds) by apparent plant size in the 2D image and the 2D spatial planting pattern along the crop row are used (e.g., Åstrand and Baerveldt 2005; Onyango and Marchant 2003; Southall et al. 2002; Tillett et al. 2001, 2008). These techniques are fairly effective during the early portion of the growing season, when weed control is most critical, before canopy closure has occurred and the 2D silhouettes of the plants have not yet merged. For robust performance they require a uniform and well-established crop stand and a relatively low weed density, and perform best when applied to a transplanted crop where the crop plants are larger than and more easily distinguished from weeds. The technique is better suited for the control of a robotic hoe than a sprayer, where the need for accurate recognition or mapping of weeds growing in close proximity to the crop is not necessary.

Weed Control Actuators

These are devices like cultivators that kill weeds by uprooting, thermal weeders like flame, lasers or steam that kill the weeds by destroying plant membranes, abrasives that physically degrade weed foliage, and mowers that cut weeds. Weed detection systems and processors signal the actuator to control the weed but not the crop.

Physical Weed Removal. There are four primary methods of physical weed control that may be automated: (1) mechanical cultivation; (2) thermal weed control; (3) abrasion, i.e., bombardment with air-propelled abrasive grits; and (4) mowing. All of these methods have the advantage of being pest control devices "which work by physical means to control a pest" as defined by the U.S. Environmental Protection Agency (USEPA), and do not require registration (USEPA 2015). Weed control devices also have the advantage of being organic-compliant and therefore useful in organic settings. With the exception of air-propelled abrasive grits, all of these physical methods for weed removal have been in use for decades. Automation is a means to take a proven weed control device like a cultivator knife, and combine it with intelligent technology to create something very different—an intelligent weeder.

Intrarow Cultivation. Traditionally intrarow weeds have only been controlled by hand weeding and selective herbicides (Haar and Fennimore 2003). Cultivator tools such as finger weeders and torsion weeders are also used, but generally only remove small weeds (Cloutier et al. 2007, van der Schans et al. 2006). Growers and researchers have been searching for a way to remove weeds from the intra-row space mechanically without damaging the crop (Cloutier et al. 2007; Fennimore et al. 2014; Melander et al. 2015; Tillett et al. 2008; van der Schans et al. 2006).

Two designs for intelligent intrarow cultivators are currently on the market: the rotating disc design from Tillett and Hague Technology Ltd. in the United Kingdom and is being marketed as the Robocrop "In Row" cultivator (Fennimore et al. 2014; O'Dogherty et al. 2007; Tillett et al. 2008) and reciprocating knives that reach in and out of the crop row with the use of machine vision guidance (Melander et al. 2015). Both systems essentially do the same thing, but by different mechanisms. The Robocrop cultivator has a rotating disc controlled by a vision system to detect the crop plant and align the disc cutaway section with the crop plant (Figure 1). The disc rotational phase is altered as needed by changing the speed of the hydraulic drive to align the cutaway section with the crop plant to allow for variation in crop spacing (Tillett et al. 2008). Research showed that the Robocrop rotating cultivator provided effective weed control and did not injure or reduce yields in transplanted vegetable crops compared to the standard cultivator treatment (Fennimore et al. 2014). However, in seeded lettuce where plant spacing is more variable, the Robocrop injured the crop and caused 26% yield reductions, primarily due to stand reduction.

Examples of reciprocating knife type intelligent cultivators currently available for commercial use in North America include the Robovator and Steketee IC. The Robovator intelligent cultivator was also evaluated in broccoli and lettuce in comparison to a conventional interrow cultivator in California (Figure 2). The Robovator reduced the weed densities by 27 to 41% more than the standard

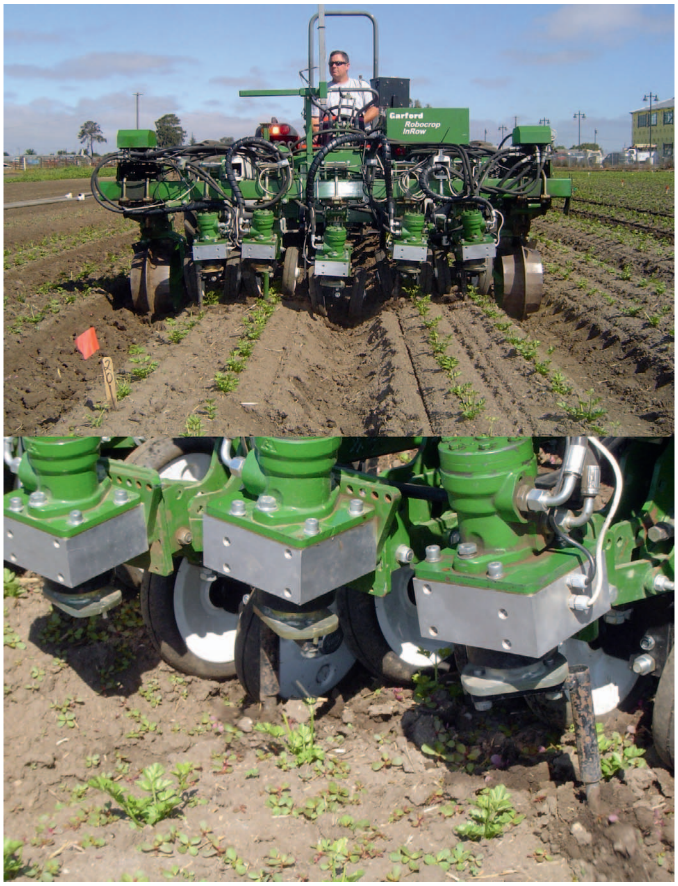

Figure 1. Robocrop intrarow cultivator used on two celery [*Apium graveolens* L. var. dulce (Mill.) DC.] beds at Salinas, CA (top). The bottom photo is a close up of the intrarow cultivation. (Color for this figure is available in the online version of this article.)

cultivator and hand-weeding times by 29 to 45% (Lati et al. 2016). They also found that broccoli and lettuce yields were not reduced by the Robovator. Another commercially available intelligent cultivator is the Steketee IC cultivator (Figure 3). Evaluations of the IC cultivator in lettuce showed that the machine found the crop row readily and detected the crop with near 100% accuracy early in the crop cycle, but fell to 54% accuracy at crop maturity (Hemming et al. 2011).

Intelligent cultivators were found to be a viable alternative to hand weeding for vegetables grown in Denmark (Melander et al. 2015). Robovator intelligent cultivator was evaluated in onion [*Allium cepa* var. *cepa* (L.)] and cabbage [*Brassica oleracea* (L.) var. *capitata* (L.)] for intrarow weed removal in comparison to a finger weeder (Melander et al. 2015). They did not see a large advantage for the

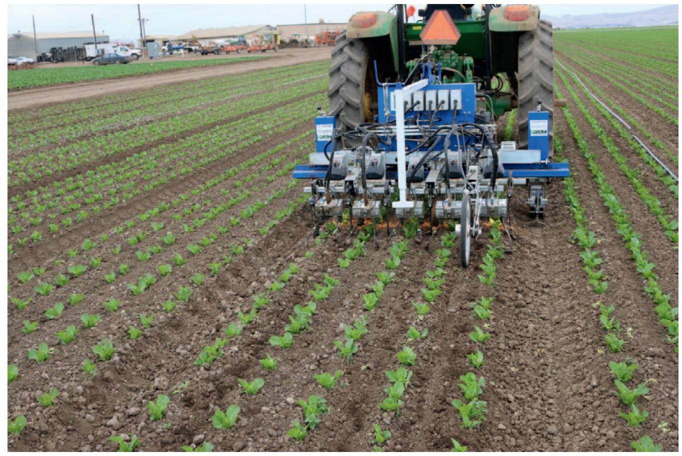

Figure 2. Robovator intrarow cultivator equipped with reciprocating knives, weeding lettuce on a 2-m-wide bed near Santa Maria, CA. (Color for this figure is available in the online version of this article.)

intelligent cultivator compared to the "nonintelligent" finger weeder in terms of weed control and crop tolerance.

Another concept for controlling intrarow weeds mechanically is "stamping." Stamping is where weeds are pushed into the ground with the use of a high-speed "ramming rod." Michaels et al. (2015) developed one such system for use in organic carrot [*Daucus carota* (L.) var. *sativa* (Hoffm.)] production. The stamping tool comprised of a cordless nail gun mechanism, which forced a 1.0-cm-diameter cylinder rod 30 cm into the soil. The stamping tool

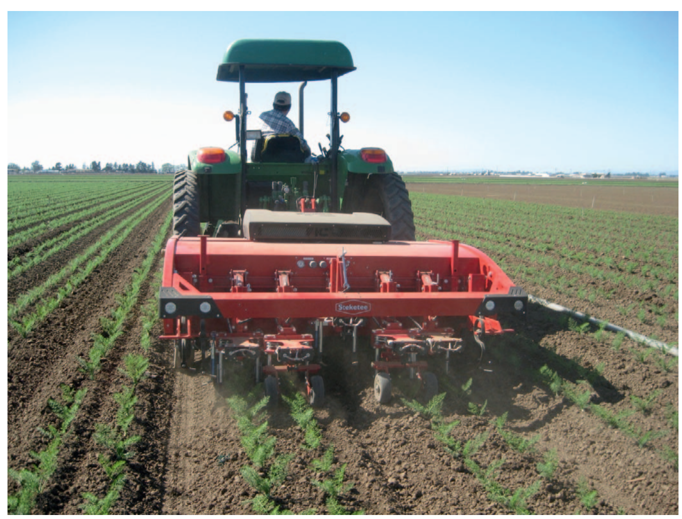

Figure 3. Steketee IC, equipped with reciprocating knives operating in a fennel (*Foeniculum vulgare* Mill.) planting near Castroville, CA. (Color for this figure is available in the online version of this article.)

https://doi.org/10.1614/WT-D-16-00070.1 Published online by Cambridge University Press

was attached to a robotic arm that allowed the device to move in the X–Y plane for precision placement. The robot was equipped with two cameras, one mounted in front of the vehicle for detecting the general location of weed plants and the second for precise positioning of the stamping tool. Although actuator positioning was generally better than 5 mm and stamping tool cycling speed was 100 ms, the maximum work rate of the system was only 1.75 weed/s^{-1} at a speed of 3.7 cm/s^{-1}.

Thermal Weed Control. Flame weed control, used in organic and conventional cropping systems, is a process of exposing plant tissues to flames coming from a burner normally fueled by propane. Flaming controls weeds by heating rather than burning plant tissue. Propane burners can generate combustion temperatures of up to 1,900 C, which raises the temperature of the exposed plant tissues rapidly. Heat injury results in destruction of plant membranes, which results in loss of cell function, and eventually the plants die or are severely weakened. During the 1960s, flaming was widely used in the United States for weed control in cotton (*Gossypium hirsutum* L.), maize (*Zea mays* [Schrad.] Iltis), sorghum [*Sorghum bicolor* (L.) Moench], soybean [*Glycine max* (L.) Merr.], potato (*Solanum tuberosum* L.), and other crops. During the 1960s and the 1970s, flaming was replaced by the use of herbicides because of an increase in propane price and the availability of less expensive herbicides. Recently, concerns about herbicide impacts on the environment have renewed interest in flame weed control (Knezevic et al. in press).

The use of automated flamers for intrarow weed removal remains an area to be explored (Nørremark et al. 2009). A prototype automated flamer for intrarow weed removal is under development in Denmark by Poulsen Aps (Poulsen 2011). The basis of this machine is serial application of a flame fueled by propane. As the flamer passes over a weed, the machine vision system turns on the burners so that a specific weed will receive multiple exposures to the heat. The machine vision system turns off the flame as it passes over the crop. The potential for use of precision steam application to control weeds either by precision foliar application to control weeds or to disinfect soil killing weed seed prior to crop planting remains to be explored (Knezevic et al. in press).

Hot Oils. A robotic system for precision, pulsed-jet, microdosing of high-temperature, organic, food-grade oil for intrarow weed control in vegetable crops was developed by Zhang et al. (2012b) at the University of California, Davis. This robotic system has two unique features. First, it was capable of distinguishing tomato plants from weeds, including black nightshade, with above 95% accuracy with the use of an advanced sensing system that used hyperspectral imaging and a Bayesian classifier based upon machine learning for real-time species recognition. Second, the robotic pulsed-jet, microdosing system (the actuator) could target individual weed leaves with a lethal dose of high-temperature (160 C) oil with a 1-cm spray resolution. The target application rate to weed leaf surface was 0.85 mg cm^{-2} of the thermal fluid, applied in 10-ms-pulsed doses, which achieved above 93% weed control at 15 d after application with less than 3% of tomato plants injured by the treatment. Commercial development potential is unknown.

Laser Weeding. Weed control using laser technology has been investigated by several researchers as a nonchemical/organic weed method for management. Mathiassen et al. (2006) studied the potential of commercially available laser systems for controlling three weed species: common chickweed (*Stellaria media* L.), scentless mayweed [*Tripleurospermum inodorum* (L.) Sch. Bip.], and oilseed rape (*Brassica napus* L.). Two different types of continuous-wave diode lasers were used to target the apical meristems of weeds at the cotyledon stage. Weed control efficacy varied significantly and depended on weed species, wavelength, exposure time, spot size, and laser power. Of the systems tested, only the 5-W, 532-nm laser with 1.8-mm spot size configuration effectively controlled all three weed species. Energy and exposure times required for this configuration ranged from 1.3 to 9.9 J, with corresponding exposure times of 250 to 2,000 ms. Further research is needed to determine the efficacy on a broader spectrum of weed species.

Kaierle et al. (2013) also experimented with using lasers for nonchemical weed control. They investigated four types of lasers at different wavelengths: CO_2 (10,600 nm), fiber (1,908 nm), diode (940 nm), and solid-state (532 nm). The lasers were used to irradiate the apical meristem of redroot pigweed (*Amaranthus retroflexus* L.) at the first true leaf stage of growth. Three different laser positions and three spot sizes 3.0, 4.2, and 6.0 mm were used to investigate the impact of local or systemic irradiation on plant damage. Minimum lethal doses of energy ranged from 10 to 71 J weed^{-1} with the lowest energy requirements resulting from use of the CO_2 laser. Laser positioning was found to be important, as a damage model showed a required energy increase of 1.3 J for every 1% loss in positioning accuracy.

Abrasion. Air-propelled abrasive grit material has been evaluated as a weed control device directed at the base of corn, soybean, or vegetables (Forcella 2009, 2012, 2013; Wortman 2014, 2015). Similar methods have been evaluated in the Netherlands with pneumatic air blasting (van der Schans et al. 2006). Currently there is research to pair abrasion with intelligent technology, but to the best of our knowledge there are no published reports yet (Manuel Perez Ruiz, personal communication).

Mowing. The main area where autonomous mowers have been utilized is for mowing lawns (Melita et al. 2013). Traditionally, autonomous lawn mowers have utilized a wire guidance system that sets the boundaries for the area to be mowed. However, a project to develop highly accurate GPS guidance for autonomous lawn mowers is in progress in Europe (Melita et al. 2013). Traditionally mowing has been used for weed control in orchards, vineyards, and pastures (Cloutier et al. 2007). There would appear to be potential for use of autonomous mowers for weed control in all of these areas. There has been some research in Denmark to develop an autonomous mower for weed control in Christmas tree plantations (Have et al. 2005). It would appear that the potential exists for further development of autonomous mowing vehicles for several applications in orchards, vineyards, and pastures.

Precision-Spray Application. Precision spraying is where small volumes of herbicidal spray are directed to areas near the crop plant to control weeds. Precision-spray assemblies are typically coupled with machine vision systems to form an automated, precision-spray weeding machine. For precision-spray systems to be effective, high levels of crop/weed differentiation, accurate spray prescription maps, knowledge of sprayer tip location relative to target weed location, accurate herbicide placement, and control of spray drift are needed. Although progress and promising research has been conducted in all of these areas, the technological challenge of meeting all of these criteria has not been overcome yet. An exception to this would be the case of automated thinning machines. The following is a brief review of some of the efforts made to date for precision spray weeding systems and automated thinning technology.

One of the earliest automated precision spray weeding systems reported is the one described by Lee et al. (1999). They developed a real-time robot for controlling weeds in tomato crops. The device utilized a machine vision system for detecting plants and a sprayer capable of treating grid cell areas measuring 0.63 by 1.25 cm. When field tested at a speed of 0.22 m s^{-1}, the average error between the center of the target and spray droplets delivered was only 6.6 mm, with a standard deviation of 4.9 mm. However, the system correctly recognized only 76% of the tomato plants, and 52% of the weeds were not sprayed.

Lamm et al. (2002) used the prototype machine developed by Lee et al. (1999) as a basis for developing a precision weeding machine for cotton. Images were processed with the use of the excessive green index (ExG) for plant/nonplant segmentation and an Erosion technique for crop/weed recognition. ExG is a greenness index, calculated on a point-by-point basis in a color image as $ExG = 2 * Green - 1 * Red$, that can be used to distinguish green plant material from nongreen backgrounds like soil automatically. The Erosion image processing technique can then iteratively remove leaf-edge pixels to erase monocot weed leaves selectively while retaining dicot crop leaves (e.g., cotton) for automated crop vs. weed discrimination. When field tested at a travel speed of 0.45 m s^{-1}, the authors reported that 88% of the weeds were sprayed. Further work was needed; however, as 21% of the cotton plants were also sprayed.

Søgaard and Lund (2007) developed an autonomous robot for precision spraying. The system was tested in indoor laboratory conditions with 110-m^2 black circular disks as targets at travel speeds of 0.2 m s^{-1}. Study results showed that the system was capable of autonomously delivering microdoses (2.5 μl) of spray to targets with subcentimeter accuracy. The system was further tested in field trials planted to oilseed rape as a test weed (Søgaard et al. 2006). In the study, plant surface area was found to have a large effect on machine performance. When leaf area was greater than 100 mm^2, targeting performance was acceptable as more than 86% of weeds were sprayed. When leaf area was less than 75 mm^2, however, targeting efficiency was less than 68%. Overall, 82% of the weeds were effectively sprayed.

Nieuwenhuizen et al. (2010) developed a tractor-pulled, precision weeding machine for controlling volunteer potatoes in sugar beets. The system was principally comprised of trigger-activated cameras that recorded RGB and near-infrared (NIR) images, ultrasonic sensors, a computer and a microsprayer. Images were captured through trigger activation of the cameras by a wheel encoder. Images were processed by first detecting vegetation with an excessive green threshold, and then extracting color features for grid cells measuring 11 by 11 pixels (11 by 11 mm). A classification algorithm was used to separate volunteer potato from sugar beet in each grid cell and prescription maps measuring 11 by 40 mm were created. A microsprayer comprising five needles, each connected to hoses and fast-acting solenoid valves, was used to control weeds through emission of 20 $\pm$ 5 μl droplets of a 5% v/v solution of glyphosate. In laboratory tests, spray droplet control accuracy was $\pm$ 14 mm in the longitudinal direction and $\pm$ 7.5 mm in the transverse direction. When field tested at travel speeds ranging from 0.2 to 0.8 m s^{-1}, the study found that on average, over 99% of sugar beet plants were left unsprayed, whereas 86% of the volunteer potatoes plants were sprayed. Mortality rates for sugar beet and volunteer potato were 1% and 77%, respectively. These results are very encouraging, however, to be useful for most specialty crops, spray resolution, and weed detection accuracies greater than 11 by 40 mm will likely be needed.

Midtiby et al. (2011) developed a real-time microspraying weed control system that utilized an inkjet printer head for the spray assembly. The unit's machine vision system utilized color and shape features to identify crop and weed plants. The automated machine was tested with corn as the crop plant in a laboratory setting at speeds of 0.5 m s^{-1}. A spray solution containing a 5 g L^{-1} concentration of glyphosate was used to control weeds. Although all of the corn plants exhibited normal growth, only 37% of one of the weed species tested was effectively controlled. Potential reasons stated for this were suboptimal weed identification, problems related to depositing enough herbicide on weed leaf surfaces, or both.

Figure 4. Lettuce thinning at Salinas, CA with the BlueRiver Lettuce Bot (top) and a close-up of the newly thinned lettuce showing the sprayed zones where lettuce will be removed and unsprayed zones where "saved" lettuce plants will be grown to maturity (bottom). (Color for this figure is available in the online version of this article.)

Automated lettuce thinners can be thought of as precision-spray, intrarow weeding machines, because they remove closely spaced, undesired plants in the seed row. Currently, there are four companies that manufacture automated thinning machines in the United States. These include units from Ramsay Highlander Inc. (Gonzales, CA), Agmechtronix LLC (Silver City, NM), Blue River Technologies Inc. (Sunnyvale, CA), and Vision Robotics Corp. (San Diego, CA) A representative image of the technology is shown in Figure 4. All manufacturers use a machine vision system to locate lettuce plants for selective thinning and herbicidal spray solutions to kill unwanted plants. The machine vision systems employed are designed to locate crop plants

https://doi.org/10.1614/WT-D-16-00070.1 Published online by Cambridge University Press

primarily by using color and plant size criteria (Siemens 2014). This scheme works well, as lettuce seedlings are typically much larger than weeds at the time of thinning. In conditions where weed density is high or when weeds are comparable in color or size to that of lettuce seedlings, machine performance is less than optimal and sometimes ineffective. To minimize spray drift, spray delivery systems are housed in enclosures. Spray is delivered intermittently based on desired plant spacing and machine location through activation of fast-acting solenoids. The location of the spray nozzle relative to the lettuce plants is determined optometrically with the use of an approach similar to that described by Siemens et al. (2012), through analysis of consecutive images or a combination of both. Commercial lettuce thinners are typically used to thin small plants, roughly 1.9 cm in diameter, at speeds of 0.7 to 1.3 m s^{-1}. An example of a field where rows of lettuce have been intermittently sprayed by an automated thinner is shown in Figure 4. Average plant spacing can be as low as 3.8 cm, but plant spacing greater than 4.4 cm is preferred for optimal performance (N Abranyi, Blue River Technologies Inc., personal communication). In optimal conditions, targeting accuracy can be as low as 0.6 cm, but accuracies of around 1.3 cm are typical. Products such as fertilizer solutions, sulfuric acid and carfentrazone are successfully used to kill lettuce seedlings. Surfactants and/or antidrift agents are commonly mixed with the herbicidal solution to promote mortality of sprayed plants and prevent damage to crop plants.

Because automated thinning technology is so new, there are few reports in the literature regarding their performance or economic viability. Siemens et al. (2012) developed and evaluated a prototype automated thinning machine in lettuce at travel speeds of 0.7 m s^{-1}. As compared to the hand-thinned treatment, there were no significant differences in plant spacing, plant spacing uniformity, plant population, or time required for a hand laborer to remove plants missed during thinning. Yields were also not significantly different between the two treatments.

Chu et al. (2016) evaluated the performance of a commercial automated thinning machine in romaine lettuce. In the study, seeds were planted 6.3 cm apart and plants were thinned with the use of fertilizer solutions at the two-leaf stage of growth. Study results showed that plant size was not affected 1 wk after hand thinning and that plants were actually larger, as compared to the hand-thinning treatment 2 to 3 wk after hand thinning. A possible explanation for the larger plant size with the machine-thinned treatment was that seedling roots were not disturbed, because plants were thinned using chemicals and not by hand hoeing. The study also found that automated thinning resulted in more uniform plant spacing and increased individual plant weights. A significant yield improvement was found at one of the three test sites.

Smith et al. (2014) evaluated the performance of automated lettuce thinners and their impact on labor savings. In the study, three different automated thinners were tested in commercial lettuce fields. Like Chu et al. (2016), they also found that automated thinning improved plant spacing uniformity. Although yields were moderately higher at six of the seven test sites, automated thinners left seven times as many closely spaced lettuce plants as compared to the hand-thinned treatments. As a consequence, the time required for the subsequent hand-weeding operation, where closely spaced plants and weeds are removed, increased by 0.5 h ha^{-1}. Total labor requirements for both operations, thinning and hand weeding after thinning, however, was 1.8 h ha^{-1} lower for the automated thinner treatments because of higher labor use efficiency during thinning. Assuming an hourly wage of \$13 hr^{-1}, this translates into a \$23 ha^{-1} savings in labor costs.

These studies on automated thinning machine performance show the viability of using spray-based systems to control unwanted plants in close proximity to crop plants. In order for these technologies to be used for general-purpose weeding, improved machine vision systems that can reliably differentiate between crop and weed plants are needed. Spray systems that can accurately spot-apply herbicides to weeds at the 1-cm scale at commercially viable speeds also need to be developed if weed removal accuracy is to be improved.

Adapting Cropping Systems for Automation Technologies

Weed control technologies are commonly designed and developed to function in the existing characteristics of cropping systems, and this has been the predominant approach for mechanical weed control. Thus, equipment and operation settings are limited by factors such as planting density and arrangement, crop susceptibility to mechanical injury, crop architecture, size, and growth stage (Forcella 2012; Mohler 2001; Slaughter et al. 2008). The successful development and adoption of automation technologies for weed control would increase if consideration is given to the need to modify crop characteristics and agronomic practices to find an optimum balance between the requirements of the crop and those of automation technologies. This two-way approach, in fact, has been used for herbicide development. Although herbicide registration is done predominantly for crops that are tolerant to the herbicide, i.e., native traits, new varieties are usually released and adopted by growers only if they have the necessary tolerance to the herbicides commonly used in the crop (Leon and Tillman 2015). Row spacing in orchards and vineyards are determined not only by canopy light interception efficiency, but by machinery requirements for production practices such as pruning and harvest (Wagenmakers and Wertheim 1991). An example would be to plant orchard crops in hedgerows to facilitate operations such as mechanical harvesting and pruning (Connor et al. 2014). Cross cultivation using traditional cultivators is a very effective means of weed control and is used in crops like perennial plantings of artichoke (*Cynara scolymus* L.) (Haar et al. 2001). The potential to modify crop planting patterns to permit rapid cross cultivation has yet to be explored for most crops. For example, a cultivator set up with RTK GPS or a machine vision guidance system would be able to cultivate a field quickly in two directions, i.e., cross cultivation. Therefore, new automation technologies for weed control might need modifications in existing production practices to take full advantage of their benefits (Rask and Kristoffersen 2007).

Planting Arrangement. A major benefit of automation technologies is the increase in speed during implementation of weed control, especially mechanical practices (Tillet et al. 2008). Although weed suppression is higher as crop density increases and row and intrarow spacings decrease (Boyd et al. 2009; Teasdale and Frank 1983), control practices such as cultivation, and especially intrarow cultivation, can be greatly limited at high planting densities and narrow spacing (Mohler 2001). Thus, to ensure adequate intrarow weed control with the use of mechanical devices, it might be necessary to find an optimum planting density that does not maximize crop weed suppression, but would facilitate weed and crop detection and the implementation of the weed control actuators while ensuring high levels of weed removal and crop safety (Scarlett 2001; Slaughter et al. 2008). Another strategy is the use of small autonomous robots that identify and control weeds by using machine vision to identify weeds and a weeding tool (Åstrand and Baerveldt 2002). Autonomous vehicles that work slowly and carefully could more accurately differentiate weeds and remove them from the crop. Studies of new automation machines should evaluate not only different speeds, but also different distances between crop plants.

One new piece of technology is the "plant tape" precision transplanter (Figure 5). The system allows rapid and efficient transplanting of vegetable crops, which can facilitate precision cross cultivation (Maw and Suggs 1984; Fennimore et al. 2014). Precise and accurate placement of the transplants allows for easier plant tracking by intelligent cultivator machine vision systems, which should improve their performance.

Crop Morphology and Development. Crop damage is perhaps the main concern for growers and the most important limitation for the use of mechanical weed control tools (Pleasant et al. 1994; Vangessel et al. 1998). As explained before, automation and robotic weed control machines will be developed with the goal to minimize contact with the crop. However, it is likely that this contact will not be zero. Therefore, having cultivars that are better suited to deal with mechanical contact by these machines without suffering negative effects on growth or yield will allow the implementation of new automation technologies.

Because intrarow cultivation is necessary for adequate weed control, especially in the absence of herbicides such as in organic systems, the risk of crop root damage becomes a major limitation for this practice (Kurstjens et al. 2004; Pleasant et al. 1994). Breeding for crop plants with deeper root systems and stronger anchorage to the soil will greatly favor the development of mechanical control technologies (Kurstjens et al. 2004). The

https://doi.org/10.1614/WT-D-16-00070.1 Published online by Cambridge University Press

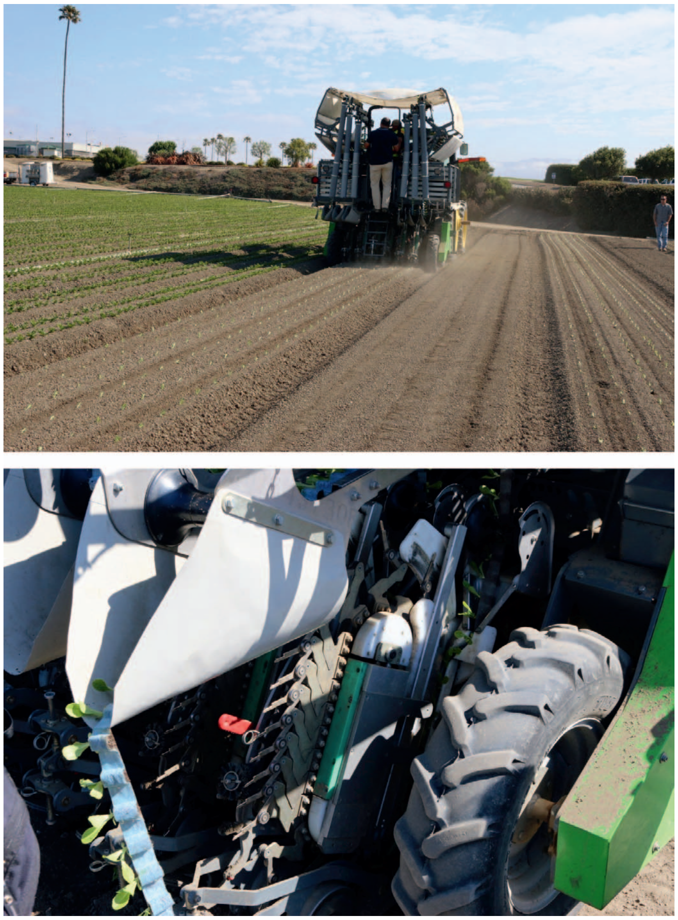

Figure 5. The Plant Tape machine transplanting lettuce with six plant lines per 2-m-wide bed (top) at Spreckles, CA. Shown on the bottom is a close up of one plant tape feeding into the transplant mechanism. (Color for this figure is available in the online version of this article.)

selection of germplasm with deeper root systems is currently under way, mainly through efforts to develop drought-tolerant varieties (Araus et al. 2002; Nibau et al. 2008). Collaborating with plant breeders is critical to identifying germplasm that will enable the use of automation technologies for weed control.

Summary

Automation of weed removal appears to be a very promising technology for specialty crop weed management programs. The ability to spray automatically or hoe weeds robotically, leaving the crop undamaged, creates opportunities to increase the efficiency of labor use in specialty crops greatly. Labor availability for hand weeding, a critical need in many specialty crops, is diminishing, and there is little prospect that new herbicides will be the remedy. Instead, advances in specialty crop weed control can be found in the area of computer processing, machine vision, and precise weed destruction. Commercial weeding machines are primarily being manufactured by European companies and startup ventures in the United States with the aim of reducing field labor costs in specialty crops. However, there is the potential for application of much of this machinery in agronomic crops, especially in organic production systems. Much of the actuator and sensor technology presented here is not new. However, what is new is the commercialization of weed removal technology that integrates sprayers or intrarow cultivators into intelligent control systems that are capable of removal of most weeds in vegetable crops (Lati et al. 2016). It is not possible to predict the future trajectory of commercial development of intelligent weed removal equipment, but it is possible to say that the economic and regulatory constraints on herbicide development are much greater than for intelligent weed removal technology. Companies that are developing intelligent weed removal technologies are relatively small compared to traditional pesticide companies, and less constrained by legacy herbicides that pesticide companies own and must defend. It appears possible that small innovative companies may be the primary source of new weed management technology in the future. Based on the vast improvements in robotics and processing, it would appear that the future of automation in weed control is very promising.

Literature Cited

Araus JL, Slafer GA, Reynolds MP, Royo C (2002) Plant breeding and drought in C_3 cereals: what should we breed for? Ann Bot 89:925–940

Åstrand B, Baerveldt A (2002) An agricultural mobile robot with vision-based perception for mechanical weed control. Auton Robots 13:21–35

Åstrand B, Baerveldt AJ (2005) Plant recognition and localization using context information and individual plant features. Paper IV *in* Vision Based Perception for Mechatronic Weed Control. Åstrand, B. PhD thesis. Chalmers University of Technology. Göteborg, Sweden. fou.sjv.se/fou/download.lasso?id=Fil-000788. Accessed on April 19, 2016

Boyd NB, Brennan EB, Fennimore SA (2006) Stale seedbed techniques for organic vegetable production. Weed Technol 20:1052–1057

https://doi.org/10.1614/WT-D-16-00070.1 Published online by Cambridge University Press

Boyd NS, Brennan EB, Smith RF, Yokota R (2009) Effect of seeding rate and planting arrangement on rye cover crop and weed growth. Agron J 101:47–51

Castello O, Gerwick C, Johnson T, LePlae PR Jr, Lo W, Roth JJ (2015) Herbicide discovery: the search for new modes of action. Proc Calif Weed Sci Soc. http://www.cwss.org/uploaded/media_pdf/947-1C_Roth_CWSS2015_Herbicide%20Discovery.pdf. Accessed April 19, 2016

Chu Q, Liu J, Bali K, Thorp KR, Smith R, Wang G (2016) Automated thinning increases uniformity of in-row spacing and plant size in romaine lettuce. HortTechnology 26:12–19

Cloutier DC, van der Weide RY, Peruzzi A, LeBlanc ML (2007) Mechanical weed management. Pages 111–134 *in* Upadhyaya MK, Blackshaw RE, eds. Non-Chemical Weed Management. Oxfordshire, UK: CAB International

Connor DJ, Gómez-del-Campo M, Rousseaux MC, Searles PS (2014) Structure, management and productivity of hedgerow olive orchards: a review. Sci Hortic 169:71–93

De Baerdemaeker J (2014) Future adoption of automation in weed control. Chapter 13 *in* Young SL, Pierce FJ, eds. Automation: The Future of Weed Control in Cropping Systems. Dordrecht, The Netherlands: Springer Science + Business Media

Duke SO (2012) Why have no new herbicide modes of action appeared in recent years? Pest Manag Sci 68:505–512

Ehsani MR, Upadhyaya SK, Mattson ML (2004) Seed location mapping using RTK GPS. Trans ASAE 47:909–914

Fennimore SA, Doohan DJ (2008) The challenges of specialty crop weed control, future directions. Weed Technol 22:364–372

Fennimore SA, Smith RF, Tourte L, LeStrange M, Rachuy JS (2014) Evaluation and economics of a rotating cultivator in bok choy, celery, lettuce, and radicchio. Weed Technol 28:176–188

Fennimore SA, Tourte LJ, Rachuy JS, Smith RF, George CA (2010) Evaluation and economics of a machine-vision guided cultivation program in broccoli and lettuce. Weed Technol 24:33–38

Forcella F (2009) Potential of air-propelled abrasives for selective weed control. Weed Technol 23:317–320

Forcella F (2012) Air-propelled abrasive grit for postemergence in-row weed control in field corn. Weed Technol 26:161–164

Forcella F (2013) Soybean seedlings tolerate abrasion from air-propelled grit. Weed Technol 27:631–635

Garrett RE, Talley WK (1969) Use of gamma ray transmission in selecting lettuce for harvest, Paper No. 69-310, The 1969 Annual Meeting of the American Society of Agricultural Engineers.

Gianessi LP, Reigner NP (2007) The value of herbicides in U.S. crop production. Weed Technol 21:559–566

Haar MJ, Fennimore SA (2003) Evaluation of integrated practices for common purslane management in lettuce. Weed Technol 17:229–233

Haar MJ, Fennimore SA, Lambert CL (2001) Economics of pronamide and pendimethalin use in artichoke during stand establishment. HortScience 36:650–653

Haff RP, Slaughter DC, Jackson ES (2011) X-ray based stem detection in an automatic tomato weeding system. Appl Eng Agric 27:803–810

Have H, Jon Nielsen J, Blackmore S, Theilby F (2005) Autonomous Weeder for Christmas Trees —Basic Development and Tests. Pesticides Research No. 97 2005 Bekæmpelsesm iddelforskning fra Miljøstyrelsen. Danish Environmental Protection Agency. http://www.unibots.com/Papers/87-7614-869-6.pdf. Accessed April 28, 2016. 77 pp

Hearn DJ (2009) Shape analysis for the automated identification of plants from images of leaves. Taxon 58:934–954

Hemming J, Nieuwenhuizen AT, Struik LE (2011) Image analysis system to determine crop row and plant positions for an intra-row weeding machine. Tokyo, Japan: Proceedings of the CIGR International Symposium on Sustainable Bioproduction. Pp 1–7

Jeschke P (2016) Progress of modern agricultural chemistry and future prospects. Pest Manage Sci 72:433–455

Kaierle S, Marx C, Rath T, Hustedt M (2013) Find and irradiate—lasers used for weed control. Laser Tech J 10:44–47

Knezevic S, Fennimore S, Datta A (in press) Thermal weed control. *In* Encyclopedia of Applied Plant Sciences. 2nd edn. http://dx.doi.org/10.1016/B978-0-12-394807-6.00235-5

Kraehmer H, Laber B, Rosinger C, Schulz A (2014) Herbicides as weed control agents: state of the art: I. Weed control research and safener technology: the path to modern agriculture. Plant Physiol 166:1119–1131

Kurstjens DAG, Kropff MJ, Perdok UD (2004) Method for predicting selective uprooting by mechanical weeders from plant anchorage forces. Weed Sci 52:123–132

Lamberth C, Jeanmart S, Luksch, Plant A (2013) Current challenges and trends in the discovery of agrochemicals. Science 341:742–746

Lamm RD, Slaughter DC, Giles DK (2002) Precision weed control system for cotton. Trans ASAE 45:231–238

Lanini WT, LeStrange M (1991) Low-input management of weeds in vegetable fields. Calif Agric 45:11–13

Lati RN, Siemens MC, Rachuy JS, Fennimore SA (2016) Intra-row weed removal in broccoli and transplanted lettuce with an intelligent cultivator. Weed Technol 30:655–663

Lee WS, Slaughter DC, Giles DK (1999) Robotic weed control system for tomatoes. Precis Agric 1:95–113

Lenker DH, Adrian PA (1971) Use of x-rays for selecting mature lettuce heads. Trans ASAE 14:894–898

Leon RG, Tillman BL (2015) Postemergence herbicide tolerance variation in peanut germplasm. Weed Sci 63:546–554

Manh AG, Rabatel G, Assemat L, Aldon MJ (2001) Weed leaf image segmentation by deformable templates. J Agric Eng Res 80:139–146

Mathiassen SK, Bak T, Christensen S, Kudsk P (2006) The effect of laser treatment as a weed control method. Biosyst Eng 95:497–505

Maw BW, Suggs CW (1984) A seedling taping machine for bare root plants. Trans ASAE 27:711–714

Melander B, Lattanzi B, Pannaci E (2105) Intelligent versus non-intelligent mechanical intra-row weed control in transplanted onion and cabbage. Crop Prot 72:1–8

Melita CD, Muscato G, Poncelet M (2013) A simulation environment for an augmented global navigation satellite system assisted autonomous robotic lawn-mower. J Intell Robot Syst 71:127–142

Michaels A, Haug S, Albert A (2015) Vision-based high-speed manipulation for robotic ultra-precise weed control. Pages 5498–5505 *in* Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference.

Midtiby HS, Mathiassen SK, Andersson KJ Jørgensen RN (2011) Performance evaluation of a crop/weed discriminating microsprayer. Comput Electron Agric 77:35–40

Mohler CL (2001) Mechanical management of weeds. Pages 139–209 *in* Liebman M, Mohler CL, Staver CP, eds. Ecological management of agricultural weeds. Cambridge, United Kingdom: Cambridge University Press

Nibau C, Gibbs DJ, Coates JC (2008) Branching out in new directions: the control of root architecture by lateral root formation. New Phytol 179:595–614

Nieuwenhuizen AT, Hofstee JW, van Henten EJ (2010) Performance evaluation of an automated detection and control system for volunteer potatoes in sugar fields. Biosyst Eng 107:46–53

Nørremark M, Griepentrog HW, Nielsen J, Søgaard HT (2008) The development and assessment of the accuracy of an autonomous GPS-based system for intra-row mechanical weed control in row crops. Biosyst Eng 101:396–410

Nørremark M, Søgaard HT, Griepentrog HW, Nielsen H (2007) Instrumentation and method for high accuracy georeferencing of sugar beet plants. Comput Electron Agric 56:130–146

Nørremark M, Swain KS, Melander B (2009) Advanced non-chemical and close to plant weed control system for organic agriculture. *In* International Agricultural Engineering Conference, Bangkok.

O'Dogherty MJ, Godwin RJ, Dedousis AP, Brighton LJ, Tillett ND (2007) A mathematical model of the kinematics of a rotating disc for inter- and intra-row hoeing. Biosyst Eng 96:169–179

Onyango CM, Marchant JA (2003) Segmentation of row crop plants from weeds using colour and morphology. Comput Electron Agric 39:141–155

Pérez-Ruiz M, Slaughter DC, Gliever CJ, Upadhyaya SK (2012a) Automatic GPS-based intra-row weed knife control system for transplanted row crops. Comput Electron Agric 80:41–49

Pérez-Ruiz M, Slaughter DC, Gliever C, Upadhyaya SK (2012b) Tractor-based real-time kinematic–global positioning system (RTK-GPS) guidance system for geospatial mapping of row crop transplant. Biosyst Eng 111:64–71

Persson M, Åstrand B (2008) Classification of crops and weeds extracted by active shape models. Biosyst Eng 100:484–497. DOI: 10.1016/j.biosystemseng.2008.05.003

Pleasant JM, Burt RF, Frisch JC (1994) Integrating mechanical and chemical weed management in corn (*Zea mays*). Weed Technol 8:217–223

Poulsen, F. (2011) System for selective treatment of plants in a row. U.S. patent 8,027,770 B2

Rask AM, Kristoffersen P (2007) A review of non-chemical weed control on hard surfaces. Weed Res 47:370–380

Rüegg WT, Quadranti M, Zoschke A (2007) Herbicide research and development: challenges and opportunities. Weed Res 47:271–275

Scarlett AJ (2001) Integrated control of agricultural tractors and implements: a review of potential opportunities relating to cultivation and crop establishment machinery. Comput Electron Agric 30:167–191

Shaner DL (2000) The impact of glyphosate-tolerant crops on the use of other herbicides and on resistance management. Pest Manage Sci 56:320–326

Siemens MC (2014) Robotic weed control. Pages 76–80 *in* Proceedings of the California Weed Science Society. Vol. 66. Salinas, CA: California Weed Science Society.

Siemens MC, Herbon R, Gayler RR, Nolte KD, Brooks D (2012) Automated machine for thinning lettuce—evaluation and development. ASABE paper No. 12-1338169. St. Joseph, MI: ASABE. P 14

Slaughter DC, Chen P, Curley RG (1999) Vision guided precision cultivation. Precis Agric 1:199–216

Slaughter DC, Giles DK, Fennimore SA, Smith RF (2008) Multispectral machine vision identification of lettuce and weed seedlings for automated weed control. Weed Technol 22:378–384

Smith R, Mosqueda, E, Shrestha A, Galva, F (2014) Evaluation of automated lettuce thinners. Salinas Valley Agriculture–ANR Blogs. Davis, CA: University of California, Davis. http://ucanr.edu/blogs/blogcore/postdetail.cfm?postnum=15932. Accessed April 28, 2016

Søgaard HT (2005) Weed classification by active shape models. Biosyst Eng 91:271–281

Søgaard HT, Lund I (2007) Application accuracy of a machine vision-controlled robotic micro-dosing system. Biosyst Eng 96:315–322

Søgaard HT, Lund I, Graglia E (2006) Real-time application of herbicides in seed lines by computer vision and micro-spray system. ASABE paper No. 06-1118, pp. 9. St. Joseph, MI: ASABE

Southall B, Hague T, Marchant JA, Buxton BF (2002) An autonomous crop treatment robot: Part I. A Kalman filter model for localization and crop/weed classification. Int J Robot Res 21:61–74

Sun H, Slaughter DC, Perez-Ruiz M, Gliever C, Upadhyaya SK, Smith RF (2010) RTK GPS mapping of transplanted row crops. Comput Electron Agric 71:32–37

Taylor JE, Charlton D, Yunez-Naude A (2012) The end of farm labor abundance. Appl Econ Perspect Policy 34:587–598

Teasdale JR, Frank JR (1983) Effect of row spacing on weed competition with snap beans (*Phaseolus vulgaris*). Weed Sci 31:81–85

Tillet ND, Hague T, Grundy AC, Dedousis AP (2008) Mechanical within-row weed control for transplanted crops using computer vision. Biosyst Eng 99:171–178

Tillett ND, Hague T, Miles SJ (2001) A field assessment of a potential method for weed and crop mapping on the basis of crop planting geometry. Comput Electron Agric 32:229–246

Upadhyaya SK, Ehsani M, Mattson ML (2003) Method and apparatus for ultra precise GPS-based mapping of seeds or vegetation during planting. U.S. Patent 6,553,312

Upadhyaya SK, Ehsani M, Mattson ML (2005) Method and apparatus for ultra precise GPS-based mapping of seeds or vegetation during planting. U.S. patent 6941225

[USDA] U.S. Department of Agriculture (2016) What is a Specialty Crop? https://www.ams.usda.gov/services/grants/scbgp/specialty-crop. Accessed April 28, 2016

[USEPA] U.S. Environmental Protection Agency (2015) Pesticide Registration Manual: Chapter 13—Devices. http://www.epa.gov/pesticide-registration/pesticide-registration-manual-chapter-13-devices. Accessed January 23, 2016

[USGS] U.S. Geological Survey (2016) Global Positioning Application and Practice. http://water.usgs.gov/osw/gps/. Accessed March 25, 2016

van der Schans D, Bleeker P, Molendijk L, Plentinger M, van der Weide R, Lotz B, Bauermeister R, Total R, Baumann DT (2006) Practical Weed Control in Arable Farming and Outdoor Vegetable Cultivation without Chemicals. PPO Publication 532. Applied Plant Research, Wageningen University, Lelystad, the Netherlands. 77 pp

Vangessel MJ, Schweizer EE, Wilson RG, Wiles LJ, Westra P (1998) Impact of timing and frequency of in-row cultivation for weed control in dry bean (*Phaseolus vulgaris*). Weed Technol 12:548–553

Wagenmakers PS, Wertheim SJ (1991) Planting systems for fruit trees in temperate climates. Circ Rev Plant Sci 10:369–385

Wortman S (2014) Integrating weed and vegetable crop management with multifunctional air-propelled abrasive grits. Weed Technol 28:243–252

Wortman S (2015) Air-propelled abrasive grits reduce weed abundance and increase yields in organic vegetable production. Crop Prot 77:157–162

Zhang Y, Slaughter DC (2011) Hyperspectral species mapping for automatic weed control in tomato under thermal environmental stress. Comput Electron Agric 77:95–104. DOI: 10.1016/j.compag.2011.04.001

Zhang Y, Slaughter DC, Staab ES (2012a) Robust hyperspectral vision-based classification for multi-season weed mapping. J Photogramm Remote Sens 69:65–73. DOI: 10.1016/j.isprsjprs.2012.02.006

Zhang Y, Staab ES, Slaughter DC, Giles DK, Downey D (2012b) Automated weed control in organic row crops using hyperspectral species identification and thermal micro-dosing. Crop Prot 41:96–105

Received April 28, 2016, and approved July 4, 2016.

Associate editor for this paper: Robert Nurse, Agriculture and Agri-Food Canada.

https://doi.org/10.1614/WT-D-16-00070.1 Published online by Cambridge University Press