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Autonomous robotic weed control systems: A review

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ABSTRACT

Autonomous robotic weed control systems hold promise toward the automation of one of agriculture's few remaining unmechanized and drudging tasks, hand weed control. Robotic technology may also provide a means of reducing agriculture's current dependency on herbicides, improving its sustainability and reducing its environmental impact. This review describes the current status of the four core technologies (guidance, detection and identification, precision in-row weed control, and mapping) required for the successful development of a general-purpose robotic system for weed control. Of the four, detection and identification of weeds under the wide range of conditions common to agricultural fields remains the greatest challenge. A few complete robotic weed control systems have demonstrated the potential of the technology in the field. Additional research and development is needed to fully realize this potential.

1. Introduction

1.1. Importance of weed control in crop production

Weed control is a significant issue in agricultural crop production. Weeds compete with crop plants for moisture, nutrients and sunlight and can have a detrimental impact on crop yields and quality if uncontrolled. A number of studies have documented the yield loss associated with weed competition. Monaco et al. (1981) reported 71%, 67%, 48%, and 48% yield reductions in direct-seeded tomato when jimsonweed (*Datura stramonium* L.), tall morning glory (*Ipomoea* L.), common cocklebur (*Xanthium strumarium* L.), and large crabgrass (*Digitaria sanguinalis* (L.) Scop.), respectively, were present in the row at a density of 11 weed plants/m^2. Roberts et al. (1977) found that season-long competition from mixed stands of grass and broadleaf weeds at 65 weeds/m^2 resulted in complete loss of marketable lettuce in field studies in England. Lanini and Le Strange (1991) found that season-long weed competition in California lettuce fields reduced lettuce yields by over 50% and Shrefler et al. (1996) found that competition from spiny amaranth (*Amaranthus spinosus* L.) in lettuce fields reduced head weight and quality. Hodgson (1968) found that two Canada thistle (*Cirsium arvense* (L.) Scop.) shoots/m^2 reduced wheat yields by 15%. The presence of weeds at harvest may interfere with some types of harvesting techniques or defoliation of cotton. The presence of weed seed in the harvested grain or staining of cotton fiber by contact with weeds at harvest can reduce the quality and value of the crop.

A number of factors affect the magnitude of yield and quality loss including, competitiveness of crop and weeds present, density of crop and weed plants, time of emergence of the weeds relative to the crop, duration of the weed presence, and proximity of the weeds relative to the crop plants (Weiner, 1982; Pike et al., 1990). For example, Keeley and Thullen (1989, 1991) found that when Johnsongrass (*Sorghum halepense* L.) or barnyardgrass (*Echinochloa crus-galli* L.) were allowed to compete with cotton during the first 9 weeks after emergence, and then the fields were kept weed-free for the remainder of the season, yield losses of 60% and 69%, respectively were observed. Heisel et al. (2002) studied the effect of weed (*Sinapis arvensis* L. or *Lolium perenne* L.) proximity (2, 4 or 8 cm from the

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crop) on yield loss in sugar beet. The yield increased an average of 20% (independent of weed species) as the distance between the weed and crop increased from 2 to 8 cm. These factors have a direct impact on weed control: the weeds that are most difficult to remove with a hoe, for example, are also those that are most detrimental to crop yield, weeds that emerge just prior to or with crop emergence (assuming direct-seeded crops) are the most critical to remove, and infestations where there are large numbers of weeds relative to the crop (e.g. when crop germination is poor) are most harmful to yield.

Currently, for row crops, typical weed control methods include a combination of preemergence herbicide application and/or preemergence tillage, mechanical cultivation, postemergence herbicide application (if selective herbicides or crop resistance is available) and hand hoeing. While herbicide-based weed control may be both biologically efficacious and economically effective, in many situations it is not without environmental costs. In many locations, increasing pesticide use regulations, consumer concerns, and a growing interest in organically produced foods limit the long-term acceptability of herbicide application. When selective postemergence herbicides are unavailable or ineffective, hoeing of “in-row” weeds is required. However, in-row hand hoeing is costly, i.e., over five times more expensive than conventional cultivation (Chandler and Cooke, 1992) and not completely effective. Vargas et al. (1996) observed that hand-hoeing crews mistake weeds for crop plants or miss weeds, eliminating only about 65–85% of the weeds depending upon the level of field supervision and the similarity in appearance between the crop and the weeds. Weed infestations are often distributed non-uniformly in agricultural fields. The non-uniformity in weed populations has both temporal and spatial aspects that provide an opportunity for the application of site-specific weed control technology to reduce environmental and economic costs associated with weed control. Thompson et al. (1991) concluded that although the technology for tractor-mounted real-time weed detection and control did not exist, the concept of automated selective spraying of weeds in agricultural fields had great potential for reducing economic and environmental costs while maintaining a high level of weed control.

1.2. *General system design and architecture for automatic weed control*

Harrell et al. (1988) observed that an agricultural robot incorporates three basic components: “(1) a sensing system to measure important physical and biological properties of the agricultural system; (2) decision-making capabilities for processing information from the sensor system to determine how the agricultural system should be manipulated; and (3) actuators to manipulate the agricultural system accordingly.” Technologies such as machine vision analysis, global positioning systems, variable rate application techniques, and robotics provide the technological tools to allow robotic weed control to be feasible. This paper will review the current status of core technologies required for successful implementation of an autonomous mobile agricultural robot for weed control in row crops. A general-purpose autonomous robotic weed control system has four core technologies (Fig. 1): guidance (Real-time Kinematic Global Positioning System (RTK GPS) or machine vision), weed detection and identification (machine vision, hyperspectral imaging, possibly assisted by RTK GPS), precision in-row weed control (micro-spray, cutting, thermal, electrocution), and mapping (GPS & machine vision).

2. Core technologies for autonomous robotic weed control in row crops

2.1. *Row guidance systems*

2.1.1. *Machine vision-based automatic row guidance*

After decades of research and development, row crop guidance has achieved a high level of automation and some commercial success. While many guidance-sensing technologies have been attempted (e.g., Jahns, 1983; Tillett, 1991) two types of sensors have achieved the greatest commercial success: machine vision and global positioning systems. Åstrand (2005) lists the following requirements for row guidance systems:

- Ability to track rows with an accuracy of a few centimeters.
- Ability to control a row cultivator and an autonomous agricultural robot in real-time, which means that both heading and offset of the row structure must be estimated at a sufficient[ly] fast rate.
- Ability to work on sown crops, not planted, which means that the time of emergence and the size of the crops can vary in the field. This also means that crops and weeds have about the same size in early cultivation, i.e. discrimination between crops and weed cannot be made by size only.
- Ability to work when there is high weed pressure, up to 200 weeds/m^2.
- Ability to work when plants are missing in the row. This is especially the case in [organic] fields where emergence is about 70%, which is less than in conventional fields, where the emergence usually is about 90%.

Vision systems require a guidance directrix (guiding landmark) and typically use a forward-looking view of the crop rows (Fig. 2).

One of the most commonly used machine vision methods for identifying crop rows is based upon the Hough (1962) transform. The Hough transform is a computationally efficient procedure for detecting discontinuous lines or curves in pictures, thus it is suited for situations like those listed by Åstrand (2005) where the crop stand is incomplete with gaps in the crop rows due to poor germination, insect damage or other factors that result in missing crop plants in the row (Duda and Hart, 1972). This technique was proposed by Reid and Searcy (1986) to facilitate row identification for agricultural guidance and was employed by Fujii and Hayashi (1989) in their U.S. patent for automatic guidance of a combine harvester. In one of the early implementations, Marchant and Brivot (1995) used the Hough transform for row tracking in real-time (10 Hz) and noted that their technique was tolerant to outliers (i.e. weeds) only when the number of outliers was reasonably small compared to the number of true data points. Marchant et al. (1997) reported an overall RMS error of 20 mm in lateral position at a travel speed of 0.7 m/s using this technique to guide an agricultural vehicle in a transplanted cauliflower field.

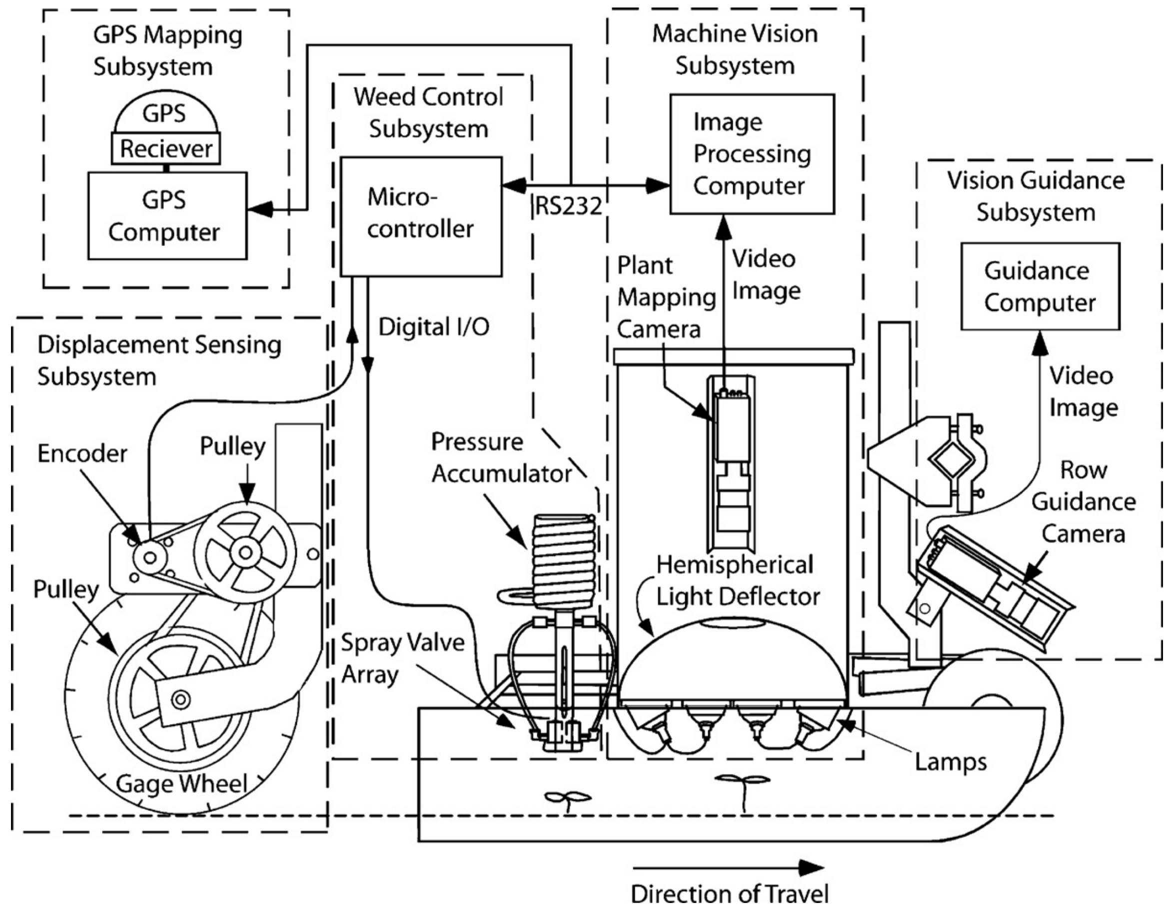

Fig. 1 – General autonomous real-time intra-row weed control system concept (adapted from Lee et al., 1999).

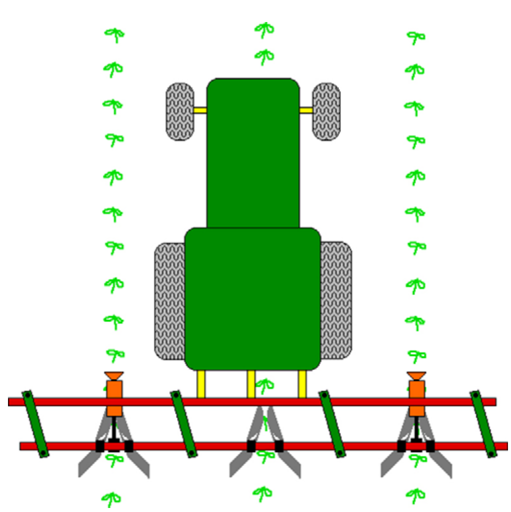

Fig. 2 – Schematic top view showing the steerable cultivation tool with two guidance cameras attached 3 m apart to provide robust performance in widely spaced row crops (e.g. processing tomatoes) under conditions where sections of the row may be missing crop plants (Slaughter et al., 1999).

Several other techniques have been investigated for machine vision guidance. Billingsley and Schoenfisch (1997) used linear regression in each of three crop row segments (or "viewports") and a cost function analogous to the moment about the best fit line to detect lines fit to outliers (i.e. noise and weeds) as a means of identifying row guidance information and indicated an accuracy of 20 mm using this technique. Slaughter et al. (1996, 1999) developed a machine vision guidance system using real-time color segmentation of direct-seeded crops (cotton, lettuce, tomato) at the cotyledon to fourth true leaf stages based upon the median of the spatial distribution of plants about the seedline. To provide accurate guidance when there were significant numbers of missing crop plants in the seedline due to poor germination, two cameras, viewing two separate crop rows 3 m apart were used. The system was tested in commercial fields at weed populations up to three weeds per crop plant and at travel speeds up to 16 km/h. The overall RMS position error ranged from 4.2 mm under no weed conditions to 12 mm under high weed loads. Tillett and Hague (1999) developed a machine vision guidance system for cereal crops, using 15 row midpoints extracted from a single view of three adjacent crop rows (five midpoints per row). They tested the system in a single barley field with light to moderate weed pressure under uniform natural lighting conditions and obtained a standard error in hoe position of 13 mm at travel speeds up to 6 km/h.

Kise et al. (2005) developed a near infrared stereovision guidance system. The lateral error of the system was 30–50 mm RMSE depending upon speed and row curvature. The method required some weed-free areas to provide sufficient information to support the stereovision-based system to detect the navigation points. Åstrand and Baerveldt (2005a) developed a machine vision guidance system for use in direct-seeded crop plantings that was robust to differing crop plant size (cotyledon to mature plants) and the presence of weeds at densities up to 200 weeds/m^2. Their method, based upon the Hough transform, used multiple rectangular regions (one for each row viewed) with rectangle width adjusted for crop size. The information from multiple rows was fused together to obtain a common estimate of the row position. Field tests conducted in commercial sugar beet fields with 6, 9, and 18 row cultivators at speeds ranging from 2.5 to 4.5 km/h and weed densities up to 50 weeds/m^2 gave a standard deviation of position error of 27 mm.

To make the machine vision system more robust to shadows, Hague and Tillett (2001) used analysis of the periodic near infrared intensity function in a lateral path across five wheat rows in a plan view of the field rather than a traditional row segmentation method to obtain row guidance information. They obtained an RMS position error of 15.6 mm at a travel speed of 5.8 km/h, no mention of weed density was made. Using a color camera, Søgaard and Olsen (2003) also developed a machine vision guidance method that did not require a plant segmentation step, replacing it with a less computationally intensive computation of center of gravity for row segments in the image and weighted linear regression to determine the position and orientation of the row.

Søgaard et al. (2002) conducted tests of two commercial machine vision guidance systems in two crops, feeding beets and rape, at travel speeds from 5 to 10 km/h, and weed pressures up to 500 weeds/m^2. They observed guidance standard deviations ranging from 11 to 22 mm. The results were comparable to performances observed in several research studies discussed earlier.

2.1.1.1. Regional differences in environment and farming practices and their impact on machine vision. In comparing machine vision algorithms, it is important to understand regional conditions (environment and farming practices) when assessing their global suitability. For example, most machine vision guidance algorithms that are developed for use in weedy row crop fields at the time of first cultivation assume that the weeds have a random spatial distribution with respect to the seedline. For regions where crops obtain their water supply from natural rainfall, this assumption is fairly reasonable, with the main exception being where the weed species and soil conditions favor distinct weed patches. An example of a situation where this assumption often fails is in California direct-seeded crops like tomato with small seeds (requiring shallow planting depths) on farms that use split-bed furrow irrigation to supply water for crop germination and initial growth. In this situation, the seedline is offset close to one edge of the planting bed and the applied soil moisture is not uniform across the bed at the time of germination, frequently resulting in a non-uniform spatial distribution of weeds with respect to the seedline.

Another difference in farming practices that can impact machine vision guidance is the use of transplanted versus direct-seeded crops and the use of a narrow band of preemergent herbicide in the seedline. When transplants are used, the crop stand is typically very uniform and the crop plants are generally much larger than the emerging weeds at the time of first cultivation. Since most machine vision guidance systems don't distinguish between crop and weed plants, methods, like the Hough transform, depend upon the crop foliage being the dominant visual pattern in the image, a condition that is easily met in transplanted cropping situations. However, in cases where a narrow band of preemergent herbicide is applied to the seedline in a direct-seeded crop, there can be dense bands of weeds at the edges of the strip of land where the preemergent herbicide was applied. Depending upon the species present and growing conditions, these weeds may exceed the crop in plant height or foliage density. Further, because the soil herbicide was applied in a linear strip, the weeds growing at the edge of these bands can have a linear row-like pattern that can be mistaken by a machine vision system for the crop row.

A farming practice unique to some arid regions is the use of a center pivot irrigation systems. Fields with center pivot irrigation require guidance systems that can track curved rows, particularly near the center of the field where the curvature is greatest. The majority of machine vision systems are designed for and evaluated in fields with straight rows.

A number of researchers (e.g., Woebbecke et al., 1995a; Tian and Slaughter, 1998; Hague and Tillett, 2001; Marchant and Onyango, 2002) have investigated methods for improving the performance of machine vision techniques for operation under varying natural illumination conditions. For example, Åstrand and Baerveldt (2005a) achieved good performance in detecting plants in near infrared images acquired under non-uniform natural illumination in Sweden by performing a grayscale opening operation on the raw near infrared image and subtracting it from the original prior to segmentation. The method is less effective for images acquired in California due to differences in natural illumination conditions. One of the differences in natural illumination between different geographic locations is the ratio of diffuse to total or global illumination (sum of direct beam and diffuse illumination). A map showing the variation in the ratio of diffuse to global irradiation on clear days for regions in Europe is shown in Fig. 3 (JRC-IES, 2006; similar information for the USA can be found at Marion and Wilcox, 1995). In many locations in northern Europe, the ratio of diffuse to global irradiation is well above 0.6, while in southern Europe the ratio approaches 0.3 and in California it is about 0.25. Weather conditions can have additional impact on the level of direct beam irradiation. As the ratio of diffuse to global irradiation decreases, shadows become darker and with the current limitations in dynamic range and signal-to-noise ratio in current camera technology used in machine vision some machine vision methods for dealing with non-uniform illumination that perform well in one region may not show similar performance in other parts of the world. New high dynamic range camera technology is being developed that may also help minimize problems with non-uniform natural illumination.

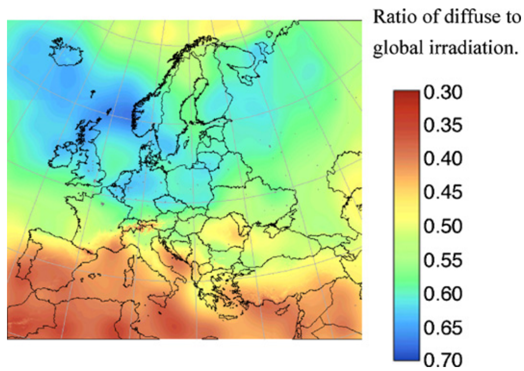

Fig. 3 – Map showing the average ratio of the diffuse to global solar irradiation levels on a clear day in Europe (JRC-IES, 2006).

2.1.2. *Real-time Kinematic Global Positioning System-based row guidance*

As an alternative, Real-time Kinematic Global Positioning Systems (RTK GPS) can provide a level of lateral positioning accuracy along the row comparable to machine vision guidance systems, trading the need for a visual guidance directrix for an unobstructed "view" of the sky from all parts of the field. GPS systems provide an absolute guidance system and in contrast to the relative guidance provided by machine vision, require that the crop be planted using an RTK GPS guided planting system or the crop rows mapped using some type of georeferenced mapping technique. RTK GPS systems also require that a GPS base station is located within approximately 10 km (6 miles) of the RTK GPS guided tractor or agricultural robot. However, since they don't depend upon the visual appearance of the crop, they are not adversely affected by weed density, shadows, missing plants or other conditions that degrade the performance of machine vision guidance systems. Another advantage of GPS guidance systems is that they can be easily programmed to follow curved rows (e.g. center pivot irrigated fields). Commercial RTK GPS automatic tractor guidance systems are generally said to be capable of steering with precision errors of 25 mm (one inch) from pass to pass in a row crop field where the RTK GPS guidance system was used to form the beds and plant the crop (e.g., Leer and Lowenberg-DeBoer, 2004). To achieve optimum guidance performance RTK GPS systems should be used in fields where there is a minimum amount of radio frequency interference, where multipath errors (due to reflection of GPS signals near the antennae) are minimal and where a minimum of four common (to the tractor and base station) satellites are available. Satellite geometry (distribution of satellites in the sky) will also affect the performance since agricultural operations typically cannot be scheduled according to optimum satellite availability.

A few researchers have documented the performance of automatic RTK GPS guidance systems in a range of agricultural applications. Stoll and Kutzbach (2000) studied the use of RTK GPS as the only positioning sensor for an automatic steering system of a self-propelled forage harvester. They found that the standard deviation of steering was better than 100 mm under all conditions. Standard deviation of lateral offset (error) along straight line paths ranged from 25 to 69 mm depending upon travel speed. Nagasaka et al. (2004) used RTK GPS for positioning, and fiber optic gyroscope sensors to maintain vehicle inclination, of an automated six-row rice transplanter. Root mean square deviation from the desired straight path after correcting for the yaw angle offset was approximately 55 mm at a speed of 0.7 m/s. The maximum deviation from the desired path was less than 12 cm. Kise et al. (2002) studied the use of an RTK GPS guidance system for control of a tractor as an autonomous vehicle traveling along a curved path. Test results for following a sinusoidal path with a 2.5 m amplitude and 30 m wavelength at 6.5 km/h showed a 6 cm RMS error with a 13 cm maximum error.

2.2. *Machine vision recognition of plant species*

A variety of visual characteristics have been used in plant species identification, and can be divided into three general categories: biological morphology, spectral characteristics, and visual texture. The earliest and most extensive work has been the remote sensing studies conducted on satellite and airborne images. Moran et al. (1997) and Lamb and Brown (2001) recently reviewed satellite and airborne remote sensing research and discuss efforts to map weeds in crops. Most of the ground-based machine vision sensing work has been conducted and evolved with the development of the personal computer. The ground-based machine vision studies reported in the literature vary widely in terms of the complexity of the visual scene (e.g. ranging from individual leaves placed on contrasting backgrounds to scenes of field plants growing in actual commercial farms), number of plants studied (many studied fewer than ten plants or leaves of each species), classification objective (i.e. a two class classifier, crop versus weeds as a group, or a multiclass classifier identification of crop and all weed species), number of uncontrolled environmental factors (e.g., natural lighting conditions, wind, etc.), image acquisition conditions (moving or stationary), suitability for real-time applications, and the level of statistical validation. The number of studies where calibration models or classifiers for ground-based machine vision plant species recognition have been tested over multiple growing seasons is very limited.

2.2.1. *Biological morphology*

In biological morphology, shape recognition can be conducted at increasing levels of abstraction: geometric, structural and semantic. Most machine vision research on plant species identification has been done at the leaf geometry level with some at the whole plant level. Biological morphology is defined as the shape and structure (as distinguished from its material composition) of an organism or any of its parts. In contrast, the term morphology as applied to image processing (i.e. image or mathematical morphology) is the application of a set of basic operations (e.g. AND, OR, MIN, MAX) to an image using a structuring element. Additional information on the topic of image morphology can be found at Serra (1982) and Soille (2003). In the 1980s, the use of image morphology for online real-time applications was generally restricted to special purpose hardware-based machine vision systems, a restriction that less frequently constrains current general-purpose CPUs.

A number of basic studies of plant species recognition based upon biological morphology have been conducted (e.g., Chi et al., 2002; Franz et al., 1991a; Guyer et al., 1986, 1993; Woebbecke et al., 1995b; Yonekawa et al., 1996). These studies have investigated a wide range of machine vision shape features for leaf edge patterns (e.g., curvature or lobe features) and overall leaf or plant shape (e.g., area, length, width, perimeter, moment, dimensionless ratios, etc.) and generally achieve high recognition rates under ideal conditions. These studies demonstrate the fundamental feasibility of using machine vision shape recognition to distinguish plant species when the shape of the entire leaf is well displayed (i.e. there is no occlusion) and the leaves are undamaged or subject to stress conditions. More detailed information can be found in the recent review of plant shape based machine vision identification by Brown and Noble (2005).

In an attempt to better deal with variability in biological morphology, Søgaard (2005) developed a method for machine vision classification of weed species based on active shape models. A classification database with shape models for 19 important weed species found in Danish agricultural fields was constructed. The shape models or templates describe the leaf shape and whole plant structure of seedlings up to the two true leaf stage. Template models were developed from color field images of individual seedlings acquired under natural illumination passing through a plastic sunlight diffuser. The classification process used a flexible template matching approach where species classification was based upon both the amount of template deformation required to obtain an optimum fit and level of match between the final deformed template and the weed being identified. Model validation results for an independent set of 100 field images of each of three weed species (shepherd's purse, *Capsella bursa-pastoris* (L.) Medik.; scentless mayweed, *Tripleurospermum* Schultz-Bip.; and charlock, *S. arvensis* L.) seedling gave classification rates from 65% to above 90%, depending on weed species.

In one of the few studies to quantify the levels of occlusion and leaf orientation where machine vision recognition begins to fail Franz et al. (1991a) studied the effect of partially occluded leaves where portions of each leaf were masked (i.e. removed) and replaced by a straight line boundary producing a truncated edge similar to that produced by the Watershed method (Vincent and Soille, 1991; Lee and Slaughter, 2004) and of leaves positioned at various non-horizontal orientations. Leaf species were correctly identified using leaf edge curvature when leaf occlusion was less than 20%, and the leaf orientation was within 30° of the horizontal imaging plane. Lee (1998) studied the impact of tomato cotyledon orientation on machine vision recognition using elongation and compactness shape features in a field study of 16 common processing tomato cultivars. Cotyledon orientation was measured at different times of the day and night; the plants were not subject to moisture stress. Lee observed that the cotyledon orientation of some cultivars changed with time of day (which was also correlated with air temperature and humidity) while others remained fairly stable. All cultivars maintained a fairly open leaf orientation (i.e. horizontal) during the day, but some began closing (i.e. assuming a more vertical leaf orientation) at dusk, with some cultivars holding their cotyledons completely vertical at night. In a separate test, Lee observed that tomato cotyledon orientation was affected by moisture stress, becoming more closed as stress levels increased. Lee determined that machine vision recognition using elongation and compactness failed when tomato cotyledon orientation was greater than 62° from the horizontal when distinguishing tomato from grass or other species with vertically oriented seedling leaves. Manh et al. (2001), in a study of green foxtail (*Setaria viridis* (L.) Beauv.) leaves, concluded that the deformable template method could identify partially occluded leaves. Their conclusion was based upon subjective visual assessment of the degree of match of the deformed templates. The level of robustness to partial occlusion is difficult to assess based on these results because only one species was used in the study, the deformed template did not appear to be attracted to the boundary between overlapped leaves in the example figure provided, and the authors stated that the method failed when the leaf tips were occluded. The technique, based upon fitting a parametric model to the leaf outline using color differences to make the model expand or contract toward the leaf edges shows potential for leaf identification under some types of leaf occlusion. Additional research is needed to better assess this potential under a wider range of occlusion conditions and plant species.

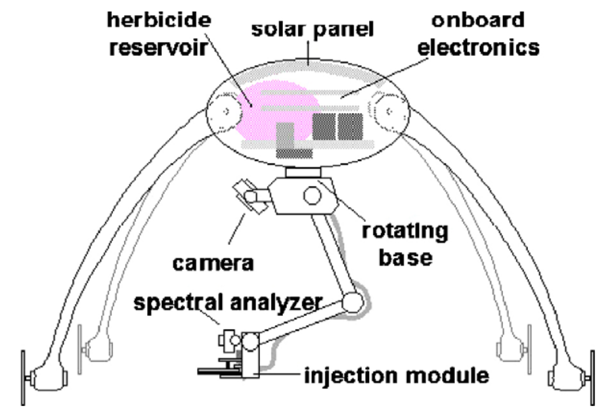

Fig. 4 – Concept diagram for a robotic weed control system with a multiple degree of freedom robotic "arm" that could allow multiple views of each plant (Concurrent Solutions, 2004).

These studies demonstrate one of the main challenges to the development of an autonomous field robot for weed control using machine vision shape recognition techniques that require leaf edge information or a leaf orientation that facilitates good leaf shape views. Human laborers in hoeing crews can easily change body positions to find an orientation that allows them to minimize visual occlusion in order to maximize the quality of the view and to gather visual information from a collection of views of each plant. In contrast, most machine vision studies have utilized a single view of each plant, limiting the amount of visual information available to the recognition process and making them more susceptible to occlusion problems. Future robotic weed control designs may incorporate multiple cameras or cameras mounted on robotic arms with multiple degrees of freedom like the system under development by Concurrent Solutions (2004, Fig. 4) that may allow multiple views of each plant to be utilized. However, multiple views result in a corresponding increase in computational requirements for analyzing multiple images and for determining the correspondence between multiple views of potentially occluded plants.

Tian et al. (1997) and Lee et al. (1999) evaluated two machine vision methods to make leaf shape based species recognition more robust to occlusion with the objective of distinguishing crop from weeds in vivo from a moving vehicle at the cotyledon and first true leaf stages. The studies were conducted as part of a robotic weed control project in direct-seeded California commercial processing tomato fields in 1994 and 1997. The 1994 study examined 30 training images and 271 validation images collected in 13 fields at 1.6–4.8 km/h travel speeds under natural sunlight using a small plastic sunlight diffuser to decrease shadows in the seedline associated with the high direct beam light levels typical of California. The 1997 study examined 26 training and 87 validation images collected in eight different fields under controlled lighting at a 0.8 km/h travel speed. More than 15 weed species were present at mostly low weed densities and partial occlusion of both tomato with tomato and tomato with weed foliage was common. The studies used color segmentation to distinguish plants from soil and simple shape based features (elongation and compactness were used in both years, while height to width and length to perimeter ratios were also used in 1994) to identify tomato cotyledons in the seedline image. Cotyledon recognition was the focus of this work because occlusion is less severe, and yield loss from weed competition is greatest in the first few weeks after emergence. It was not necessary to identify tomato first true leaves as long as the cotyledons were visible due to a buffer zone technique that prevented the robotic weed control system from damaging the first true leaves (Lee et al., 1999). Ignoring occlusion, the tomato cotyledon recognition rates for the validation image sets were 40–60% in 1994 and 62–80% in 1997, depending upon image quality, while weed recognition rates were greater than 95% in 1994 and 69% in 1997. Differences in performance between the two studies were mainly due to the use of controlled lighting in 1997 and an effort to obtain a better balance between the crop and weed classification rates.

In the 1994 study (Tian et al., 1997), a whole-plant syntactic rule based technique was evaluated in an attempt to match occluded tomato cotyledons with their unoccluded partner when possible. The method examined potential "blobs" in close proximity to recognized cotyledons in a nine-step process of elimination to identify the best match. Using this technique, the whole-plant recognition rate was 66–78% with recognition failures due either to high levels of occlusion on both cotyledons or to poor illumination. In the 1997 study (Lee and Slaughter, 2004), a modified Watershed algorithm was applied in an attempt to separate partially occluded tomato cotyledons from the occluding foliage. Blob area, compactness and the number of concave regions along the boundary were used to identify partially occluded cotyledons and determine when the Watershed algorithm needed to be applied. The recognition rate of partially occluded tomato cotyledons increased from 19 to 67% using this method. Both of these methods of dealing with partial occlusion increased the computational load on the machine vision system, and could not be implemented in real-time (3 Hz) on the personal computer systems available at the time.

While a large number of shape based methods for machine vision recognition of plants have demonstrated good potential under ideal conditions, a lack of robust methods for resolving occlusion, leaf damage or other visual "defects" (e.g., insect or hail damage, leaves twisted in the wind, or splashed with soil) commonly found in farms remains a major challenge to commercialization of the technique.

2.2.2. *Plant reflectance*

A large number of research studies have investigated the use of color or spectral reflectance techniques for plant species identification. Much of this work is described for a number of applications in three recent reviews of the topic (Brown and Noble, 2005; Scotford and Miller, 2005; Zwiggelaar, 1998). This discussion will only focus on applications for ground-based identification of plant species within the seedline. One of the greatest potential advantages of these techniques is that pixel based color or hyperspectral classifiers are robust to partial occlusion. In addition, the method tends to be less computationally intensive than shape-based techniques.

There are a large number of studies that have used various types of vegetation indices, typically ratios of broadband reflectance values in the visible and near infrared to measure crop properties. In their review, Scotford and Miller (2005) gave a list of several of the more common indices studied. Broadband color, or chromaticity values have been widely used to segment plant material from soil backgrounds (e.g., Woebbecke et al., 1995a). Many of the shape-based plant species recognition studies use color segmentation as a first step to distinguish plants from soil. Few have found high levels of success in using color segmentation alone to distinguish crops from weeds in ground-based field images. Woebbecke et al. (1995a) evaluated red, green, and blue color values as well as red and green chromaticity values, a number of color indices and hue in color images taken in a greenhouse of potted weeds and soil. They were unable to use color values to distinguish monocots from dicots. Hemming and Rath (2001) compared a machine vision classification system for cabbage, carrots and weeds using both color and biological morphology features with a classifier that used biological morphology alone. They found that in carrot fields the addition of color features to the classifier did not show clear advantages, while in cabbage there was some positive benefit.

Franz et al. (1991b) studied the use of broadband reflectance in the visible (blue, green, red) and near infrared for plant species (soybean, ivyleaf morning glory, Ipomoea hederaceae Jacq.; velvetleaf, *Abutilon theophrasti* Medik.; and foxtail, *Setaria* Beauv.) recognition of greenhouse grown plants. The mean, variance, skewness, kurtosis, third and fourth moments were calculated in a small region of the leaf near the leaf edge for each of the four wavelength regions. The average and variance of the NIR and blue values and the skewness of the red intensity distribution were selected as the best set of features to use in a classifier. When leaf orientation was controlled, the system correctly identified 45–48 observations. The accuracy decreased (50 of 66 correct) when leaf orientation was not controlled due to problems with specular reflectance. Slaughter et al. (2004) compared a broadband color classifier

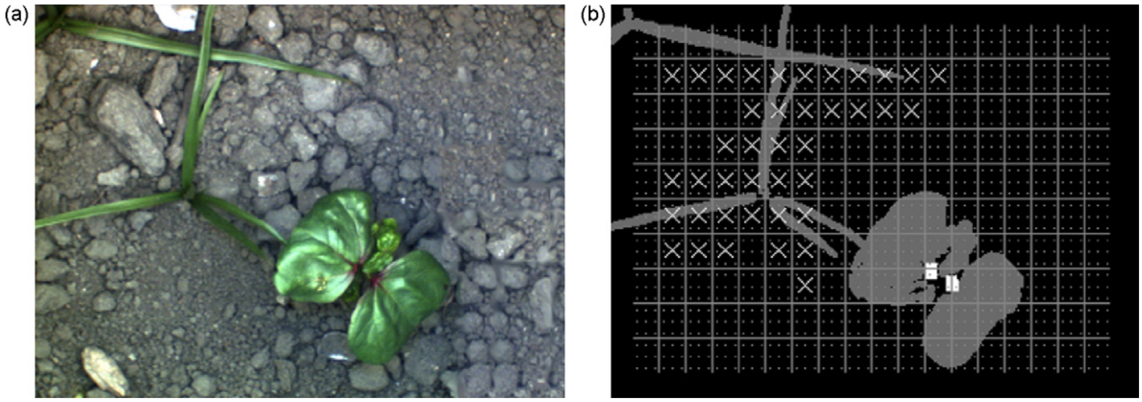

Fig. 5 – (a) Color image from a commercial cotton field showing a 'Maxxa' cotton plant with natural red pigment in the leaf tissue where the petiole attaches and a partially occluded nutsedge (*Cyperus* spp.) plant. (b) Weed map used by robotic weed control system, cells with 'X' were automatically mapped for spray by the robot (Lamm, 2000).

to a narrowband (10 nm bandwidth) visible region hyperspectral classifier to distinguish tomato from nightshade (*Solanum nigrum* L.) weeds. When the data were digitized at 8-bits/band, the color classifier had a 76% classification rate while the narrowband classifier had a 87% classification rate using one-out cross validation on 400 field grown leaf samples measured under controlled conditions in a spectrophotometer. If the data was digitized at 12-bits/band, the accuracy of the color classifier did not change, however the narrowband classifier performance improved to 95%. One of the most successful machine vision systems using color to distinguish crop from weed plants has been the autonomous robot developed by Åstrand and Baerveldt (2002) for sugar beets. In a test of 587 color images collected in several commercial sugar beet fields they found that the green chromaticity value ($g = G/[R + G + B]$) was very effective in distinguishing crop from weed plants, a 91% classification accuracy in one-out cross-validation was obtained.

In a few cases, the crop itself can have a unique visual color pattern that allows segmentation of crop and weed primarily based upon color. For example, Lamm (2000) observed that the 'Maxxa' cotton cultivar naturally contains red pigment in the cotton leaf tissue (cotyledon stage) where the petiole attaches to the leaf (Fig. 5a). He developed a special color segmentation algorithm segmenting pixels into three classes: red, green and background using excess red and excess green indices (Fig. 5b). In order to distinguish 'Maxxa' cotton from weed species also containing red pigments (e.g., purselane, *Portulaca oleracea* L.) whole-plant biological morphology was required. To achieve this, the algorithm looked for green plant leaves with a red "dot" along the leaf margin. The algorithm had a total execution time of 188 ms/image although Lamm noted this could be reduced if hardware-based color look-up-tables were utilized. An additional advantage was that the method was naturally robust to partial occlusion because the location of the red tissue was at the petiole attachment point near the center of the plant and because the algorithm did not require any leaf boundary information along the portion of the leaf most commonly occluded by other plants. Lamm noted that due to the small size of the red pigmented tissue, a high quality high-resolution color image was necessary, and a 3CCD color camera (640×480 pixel resolution) was used in their robotic weed control system to acquire images of the required quality and resolution. Two tests were conducted using color images obtained in commercial cotton fields one set (5 training images and 56 validation images) was collected with the 3CCD camera on the robot, a second set (5 training images and 85 validation images) was collected with a traditional 35 mm film camera and digitized to $640 \times 480 \times 24$-bit color images with a scanner off-line. The field where the first set was collected contained mostly nutsedge (*Cyperus esculentus* L.) weeds, while the field where the second set was collected contained mostly nightshade (*S. nigrum* L.) weeds. The validation images had a total classification error rate of 24% on the nutsedge set and 20% on the nightshade set. Errors were generally associated with color noise in the images and variation in the degree of red pigment expression in the cotton plants.

Goldsbrough et al. (1996) demonstrated the use of the *Lc* maize anthocyanin regulatory gene for study of transposon biology in tomato. The *Lc* gene determines the expression of anthocyanins in vegetative tissues and results in deeply purple colored foliage in tomato grown in sunlight. Lee (1998) conducted a field study of tomato seedlings containing the *Lc* maize anthocyanin regulatory gene demonstrating that color machine vision can be used to accurately distinguish and map crop and weed plants in real-time under heavy weed loads with partial leaf occlusion when there is a significant color contrast between the crop plants (Fig. 6). The algorithm required only 129 ms/image, allowing a robotic weed control system to travel at 0.88 m/s.

Recently, there have been several studies investigating the use of ground-based hyperspectral machine vision systems for plant species recognition. In a laboratory study of five potato plants, 12 sugar beet plants, and 25–30 plants of each of three weed species, Borregaard et al. (2000) achieved a crop versus weed classification accuracy of 89–94% using narrowband reflectance at 694 nm and 970 nm. Feyaerts and van Gool (2001) conducted a hyperspectral machine vision study of about 70 plants each of sugar beet and each of five weed species. The hyperspectral images were collected in the field and crop versus weed classification rates of 80% for sugar beet plants and 91% for weeds were observed. Vrindts et al. (2002) also

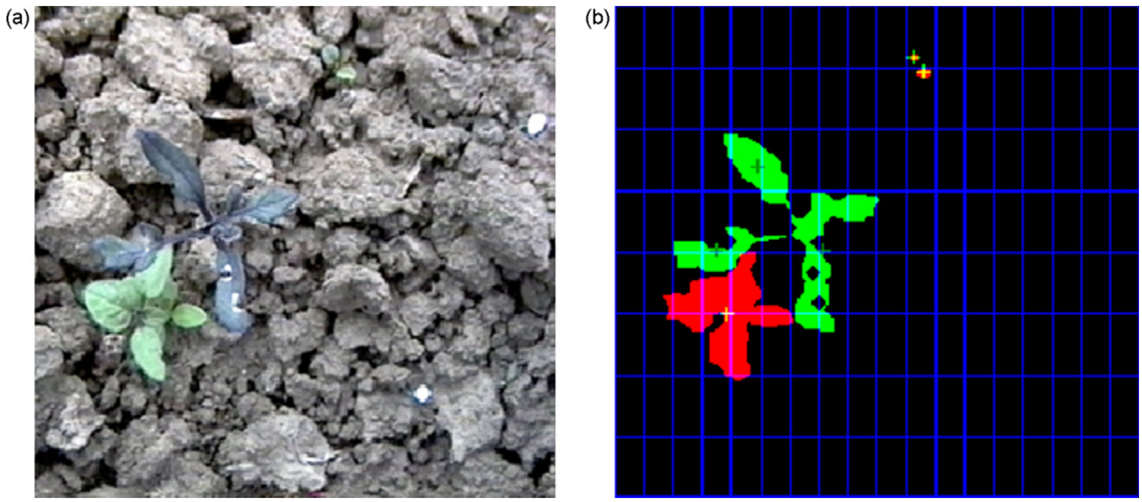

Fig. 6 – (a) Color image of a purple tomato seedling containing the *Lc* maize anthocyanin regulatory gene and two weed plants (one partially occluded). (b) Machine vision generated spray map, showing tomato plant in green and weeds in red (Lee, 1998).

used a hyperspectral machine vision system to classify sugar beet and weed plants in the field. They developed a classifier based on 970 sugar beet plant spectra and 1975 weed spectra using natural illumination that distinguished sugar beets plants from weeds at 95% and 84% accuracies, respectively. Zwiggelaar (1998) reviewed several studies on the use of spectral properties for discriminating crop plants from weeds and observed that while there was evidence that spectral properties can be used to discriminate between a certain set of crops and weeds, frequently different wavebands are selected for each crop/weed pair. Research is needed over multiple seasons to investigate the stability of multispectral classifiers for plant species recognition of field crops and weeds. Site-specific calibration techniques may be required to distinguish crops from weeds using spectral reflectance, requiring the development of adaptive learning techniques.

2.2.3. Visual texture

A few researchers have investigated the use of visual texture computed from grayscale and color images to identify plant species. Shearer and Holmes (1990) used color co-occurrence matrices in the hue saturation and intensity color space to obtain an overall classification accuracy of 91% on images of seven common cultivars of nursery stock. Shearer and Holmes mention that computation time is an important factor and suggest using a smaller set of texture features. Meyer et al. (1998) also used co-occurrence matrices on a grayscale image to compute texture features such as inertia and angular second moment to classify greenhouse grown grass and broadleaf plants with an accuracy of 93% and 85%, respectively. The texture algorithm used by Meyer et al. was computationally intensive, requiring 20–30 s/image. Burks et al. (2000a) applied the method of Shearer and Holmes to classify five weed species (ivyleaf morningglory, *I. hederaceae* Jacq.; giant foxtail, *Setaria faberi* Herrm.; large crabgrass, *D. sanguinalis* (L.) Scop.; velvetleaf, *A. theophrasti* Medik.; and common lambsquarters, *Chenopodium album* L.) grown in pots. On a test set with 20 images/species, species classification rates ranged from 90 to 95% using hue and saturation texture features and a Bayesian classifier. When divided into grass and broadleaf categories the classification rates were 98% and 95%, respectively. Burks et al. (2000b) also evaluated color texture classification on these same images using a neural network classifier and obtained similar classification rates.

2.3. *In-row weed removal mechanisms for robotic actuation*

With the development of precision planters in the 1960s, crop plant spacing down the row became much more uniform and planting skips were greatly reduced, Inman (1968). This technology allowed the development of several types of automatic thinning machines to be developed for row crops in the 1960s and 1970s. Four types of weed removal mechanisms are suited for selective in-row weed control by robotic systems: mechanical, thermal, chemical, electrical, all dating from this period.

Mechanical methods of automatically removing plants from within the seedline date from the 1960s when a number of automatic crop thinning systems were commercialized (Kepner et al., 1978). These systems (sometimes called synchronous, or selective thinners) typically used mechanically actuated switches, interrupted light beams, reflected light, or completion of an electronic circuit through the plant to earth ground to sense the location of crop plants. For plant removal two basic designs were employed: mechanical knives that could be rapidly positioned in and out of the seedline to cut unwanted plants, or a rotating hoe that could be lowered to cut unwanted plant material or raised above desired plants, sparing them. These systems are suited for use as a weed removal actuator in a weed control robot. Åstrand and Baerveldt (2002) utilized the rotating hoe type of weed control actuator in their autonomous weed control robot for sugar beets. Garrett (1966a,b) studied the accuracy with which a mechanical weed removal tool could selectively spare the desired plant while removing adjacent plants in the seedline for sugar beet, cotton, tomato, lettuce, broccoli and melon.

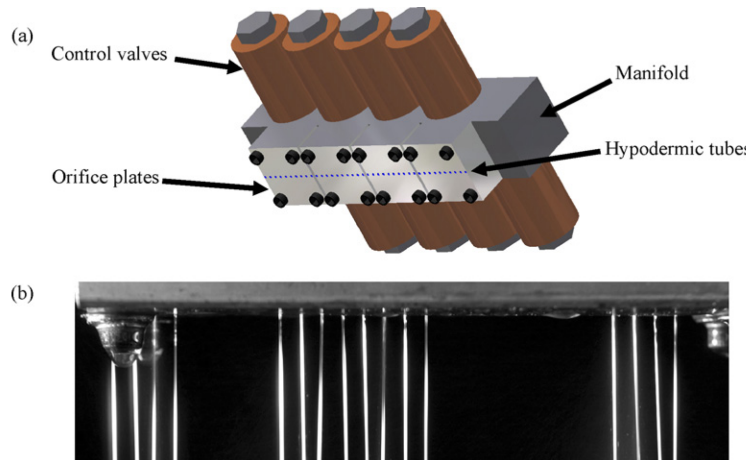

Fig. 7 – Precision spray system for treatment of seedline weeds (Giles et al., 2005). (a) Rendered drawing showing the manifold, control valves and orifice plates. (b) Side view showing the spray jets (4/valve) emitted when four of the valves are actuated.

He found that the performance was a function of the spacing between the plants, the distance along the row that is traveled (assuming that the tool is traveling along the row) between the time that the motion of the mechanical tool is initiated and the time the tool actually cuts into the row, and the accuracy with which the soil entry location of the plant to be spared is determined. Other requirements for good performance were: accurate row guidance of the device, proper height adjustment (to control the depth of cut), proper soil preparation (rolling clods in cloddy soils tended to push over plants before they could be cut), and operation timing with respect to plant age (some species become woody with age and the tool bends rather than cuts the plant).

Another design from the 1960s, called an electro-chemical thinner, used a selective spot herbicide application to kill unwanted plants (Cox and McLean, 1969). McLean (1969) made the argument that plant removal via a targeted stream of herbicide is better suited for removal of one of two adjacent plants than a mechanical blade and that spot spraying avoids soil disturbance leaving any soil herbicides in place, and minimizes physical disturbance of the plant to be spared.

A prototype precision spray system was developed by Lee et al. (1999) for use with robotic weed control systems to spray weeds in the seedline identified by machine vision. The precision spraying system consisted of a linear array of eight independent spray ports (Fig. 7). Each spray port was responsible for spraying weeds in a corresponding group of cells, each 0.63 cm × 1.25 cm in size, from a spray map generated by a machine vision system. The eight spray ports spanned a 10.16 cm width of seedline. Each spray port consisted of five hypodermic tubes (304 W stainless steel with 0.27 mm i.d.), with each tube separated by a distance of 2.5 mm across the seedline. The spray ports were approximately 15 cm above the soil surface. A micro-controller actuated-specific solenoid valves, delivering liquid to the spray ports, based on the machine vision generated weed map and robot odometry. For each spray map cell containing a weed leaf, valves were pulsed for 10 ms, resulting in a flow rate of 0.98 L/min through each spray port. The sprayer could simultaneously treat up to 8 spots across the seedline in 10 ms. Due to imprecision in the robot's odometry, a one cell crop plant buffer zone was placed around the boundary of the crop plants within the spray map to prevent inadvertent splash onto the crop when spraying nearby weeds and to compensate for some crop recognition errors. The buffer zone consisted of one grid cell (0.63 cm × 1.25 cm) encompassing and adjacent to all grid cells where the crop was identified. Lamm et al. (2002) used this prototype precision chemical application system in a test of a robotic weed control system for cotton. Field tests resulted in 11% of the weeds unsprayed and 21% of the cotton plants sprayed. System performance was evaluated immediately after depositing the spray onto weeds using a visible blue dye liquid mixture (Fig. 8). They observed that tilting or pivoting of the system during field applications might have prevented accurate targeting of spray deposition onto some weeds.

Fig. 8 – Field test of robotic weed control system equipped with a precision micro-sprayer showing blue dye selectively applied to nutsedge (*Cyperus* spp.) weeds in a cotton field (Lamm et al., 2002).

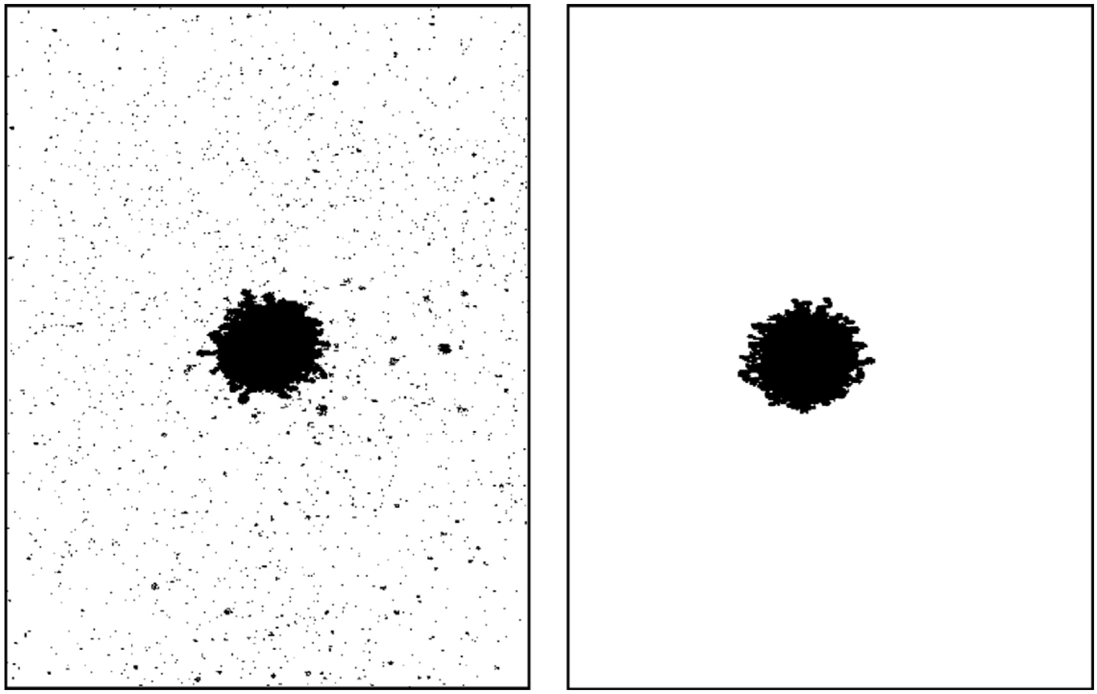

Fig. 9 – Left image shows the effect of micro-drift from a surfactant only mixture; right image shows micro-drift inhibition from a polymer surfactant mixture. Stain sizes were equivalent at 18 cm^2 for the same application conditions (from Downey et al., 2004a,b).

An advantage of the machine vision precision chemical application system is that non-selective herbicides can be used. However, inadvertent deposition (splash or "micro-drift") of non-selective herbicides on crop plants can result in significant phytotoxic damage and decreased yields. This is a valid concern since the fundamental premise of the machine vision precision spray system is to control weeds within seedlines adjacent to young crop plants that are sensitive to non-selective herbicide deposition. Downey et al. (2004a,b) evaluated the effect of splash and extent of deposition area covered, with pulsed micro-spray jets using artificial targets (Kromekote^{TM} paper). Liquid formulations included glyphosate, surfactants used to increase surface deposition for increased herbicide efficacy, and polymers that are known to inhibit splash during deposition. It should be noted that the physical configuration of the pulsed jet application, often termed "micro-spray", is actually an impinging jet (Fig. 7, Lamm et al., 2002; Giles et al., 2004) and is in effect a pulsed jet micro-dosing application. As discussed and shown by Lee et al. (1999) and Lamm et al. (2002) selective applications can be achieved within centimeter scale accuracies. The effect of micro-drift is shown in Fig. 9. The left image shows the result of a surfactant (0.25%, v/v) application from a 20 ms pulsed jet 20 cm above the target versus the right image under the same conditions except polymer (0.03%, v/v) was added to the spray mixture.

Downey et al. (2004a,b) reported that stain depositions with the silicone surfactant were five times greater than mixtures without surfactant, however associated micro-drift was extensive. This indicated that spray mixtures with surfactant require addition of a polymer for small-scale precise dosing applications. Additionally, mixtures with emulsified oil and polyacrylamide resulted in dripping from the orifice during application studies. These types of mixtures were not recommended for use with a moving precision dosing system since spray could potentially deposit on crops.

Giles et al. (2004) conducted a field bioassay experiment in a processing tomato field with pigweed (*Amaranthus albus* L., *A. blitoides* F. Watts), spotted spurge (*Chamaefyce maculate* L.) and black nightshade (*S. nigrum* L.). Weed treatments were made in a 10 cm band along the seedline based on previous machine vision system descriptions (Lee et al., 1999; Lamm et al., 2002). Spray mixtures consisted of glyphosate (0.25%, 0.375% and 0.5%; v/v), a conventional surfactant (Silwet L-77 at 0.25%, v/v) and polyethylene oxide polymer (0.00% and 0.03%). The application rate for the spray mixture was 37 μL/spray cell of 0.63 cm × 1.25 cm, resulting in an equivalent application rate of 4700 L/ha. Pulsed applications were applied to weeds similar to machine vision system applications discussed earlier; applications were made manually with an orifice to target distance of 5 cm. Phytotoxic damage to the tomatoes was observed due to micro-drift deposition of non-selective herbicide onto the tomatoes when the polyethylene oxide polymer was not used. Addition of the polyethylene oxide anti-splash polymer reduced splash and phytotoxic damage to the tomato plants. Giles et al. (2004) suggested that preventing phytotoxic damage from inadvertent splash onto the crop provided an increased yield benefit versus increasing weed control and reducing competition. This has implications for design of machine vision and treatment algorithms in that a bias towards conservative protection of the crop may be preferable to complete weed control in some situations.

Thermal weed control methods can also be used as selective plant removal tools and, like cutting methods, are suitable for organic production systems, but with the advantage of minimal soil disturbance. Flame weeding can be used as a selective weed control technique if a heat barrier, air curtain or water shield is used to protect desired plants (Lalor and Buchele, 1969; Matthews and Smith, 1969). Flame weeding is most effective when weeds are small. The equipment and fuel consumption (for the flame) tends to be more costly than herbicide application equipment and may require more trips through a field than herbicide control methods (e.g., Ascard, 1998; Laguë et al., 2001).

Selective hot water spot treatment can be used to kill young weeds without the risk of fire hazards associated with flame weeding (Daar, 1994). Several studies have shown that higher temperatures are more effective for thermal weed control (e.g., Daniell et al., 1969; Levitt, 1980). Giles et al. (2005) modified the precision spray system developed by Lee et al. (1999) for application of liquids heated up to 200 °C. The system was designed for robotic weed control using precision applications of heated organic oils to kill weeds in the seedline. Spray tests were conducted on barnyardgrass (*E. crus-galli* L.), purslane (*P. oleracea* L.) and black nightshade (*S. nigrum* L.) with oils at temperatures of 28, 100, 150 and 177 °C. At 177 °C, virtually all weeds were killed. Efficacy decreased with temperature and 150 °C was found to be the minimum temperature at which efficacy was reliable.

Considerable research has been done in the past to study the use of a high voltage (15–60 kV) electrical discharge or continuous current to kill weeds (e.g., Diprose and Benson, 1984). The method shares the advantage of minimal soil disturbance of spot spraying and does not release pesticides into the environment, trading chemical safety issues for electrical safety (both human and equipment) and fire risk (due to sparks in dry no-till conditions) issues. Unlike spot spraying, the method does require that the electrical probe(s) touch the plant, or be held in close (1–2 cm) proximity to the plant to be effective, thus treating small weed seedlings close (1–2 cm) to the soil or close to a crop plant requires precise probe position control as well as very uniform planting bed heights (e.g. no clods in order to avoid direct soil grounding or shorting of the probe(s)). Some researchers state that the activation and deactivation times are much faster than other weed control methods, but this ignores any time required to position the probe. The effectiveness reported in the literature of these methods is varied, with several giving weed control rates below 50% while others show rates above 90%. Variations in plant species characteristics, voltage and treatment methods and soil moisture levels between experiments may partially explain the differences. Blasco et al. (2002) used an end-effector with a high voltage (15 kV) electrical discharge probe to kill weeds with their robotic weed control system; the treatment (not including any sensing or positioning time) required 200 ms/weed. The system assumed that the weeds were located in a plane on the ground; no details were given regarding weed height sensing or the vertical motion control method for the end-effector.

2.4. GPS mapping systems

Global Positioning Systems are an essential tool in the application of technology for precision agriculture. Some of the commercially established precision agriculture techniques employing GPS are yield mapping, variable rate chemical applications, and the RTK GPS vehicle guidance systems described previously. GPS allows site-specific management of farming practices and resources in an attempt to optimize production efficiency while minimizing environmental costs. Two potential applications of GPS technology, seed and plant mapping, will be reviewed.

2.4.1. Automatic RTK GPS crop seed mapping systems

Researchers have studied the accuracy of automatic RTK GPS crop seed mapping systems employed during planting. Ehsani et al. (2004) propose that a crop seed mapping system can potentially facilitate plant-specific or ultra-precision farming techniques. For weed control applications, they suggest that an accurate crop seed map might be used together with a plant foliage sensor as a less computationally demanding method of weed detection than some of the machine vision techniques described previously. With this method, any plants detected at locations other than those where the crop seed was planted would be classified as weeds. These systems typically use RTK GPS for location sensing and an optical sensor to detect seeds as they are dropped into the soil at planting (Upadhyaya et al., 2003). Ehsani et al. (2004) tested the accuracy of this type of system for automatic mapping of maize seed in an agricultural field. They found, on an average, seeds were automatically mapped within 34 mm of a plant at germination (a range of 30–38 mm). In a similar study, Griepentrog et al. (2005) tested a precision seed planting system capable of automatically creating a seed map of a sugar beet field using RTK GPS for location sensing and optical seed drop sensors. They observed an average error between the automatically generated GPS seed map and the actual plant location after emergence of about 16–43 mm depending on vehicle speed and seed spacing. Location errors were attributed to the following: accuracy of the RTK GPS location system, motion of the planter relative to the GPS antennae, motion of seed after passing the optical seed sensors (e.g. seed bounce in the furrow), soil conditions (e.g. clods) that affect a deviation in the emerged plant location relative to the initial seed location. The best performance was obtained when the seed was planted with zero relative ground speed. A similar RTK GPS system for automatic plant location mapping was demonstrated by Abidine et al. (2004) for processing tomato transplants.

Søgaard and Nørremark (2004) investigated the accuracy with which sugar beet crop plants could be located by an RTK GPS controlled autonomous robot (Bak and Jakobsen, 2004) using location information from an automatically generated RTK GPS seed planting map. The autonomous robot, called the Autonomous Platform and Information system (API, Fig. 10 http://www.cs.aau.dk/∼api/) was designed to automatically acquire images, map, and possibly process images of weeds and crops in agricultural fields; while suited for a wide range of plant growth stages, a particular focus was at the seedling (cotyledon to second true leaf stage) in order to provide optimum reduction in herbicide requirements for weed control. Shortly, after emergence, the sugar beet seedlings were photographed above (i.e. a top view) by the RTK GPS mapping robot. The actual positions of 40 sugar beet plants were determined by manual inspection of the automatically acquired

Fig. 10 – Autonomous RTK GPS guided weed-mapping robot. Danish Institute of Agricultural Science, http://www.cs.auc.dk/~api.

GPS referenced images and their position compared to the seed map location. After correction for systematic errors in the travel direction the average prediction error was 16 mm, which is similar to the best performance observed in RTK GPS row guidance studies. The largest error was below 5 cm, meaning that the crop plant could be found within a region of the image with a radius of 5 cm from the recorded seed map location.

2.4.2. *Automatic GPS and machine vision weed mapping*

Weed mapping is a valuable tool for optimizing resource utilization in the management of weed control efforts. Traditionally, weed mapping is done manually, using random sampling techniques by a weed expert walking through a field. A robotic weed identification system with GPS mapping capability has the potential to automate this process, allowing increased sampling and providing more accurate estimates at low cost. For example, Downey et al. (2004a,b) described an automatic ground-based method for identifying and mapping weeds in field grown crops, using cotton as an example. The system used a digital video camera for continuous image capture along the crop seedline from a moving vehicle and simultaneously captured data from a GPS receiver. Field trials in 0.3 and 0.14 ha sample plots of two commercial cotton fields resulted in correct identification of 74% of nutsedge (*C. esculentus* L.) leaves and 92% of the cotton leaves. The primary cause for misidentification was due to occlusion, overlapping of weed and crop within the same grid cell and brown tissue damage on the cotton leaf. The automated process described represents a dramatic labor savings when compared to traditional weed scouting methods and can provide a significantly more detailed description of the percentage of weed cover in a field, particularly when high-resolution GPS systems are used. The types of maps possible with this automated system could be applied as layers in global information system (GIS) databases. Additionally, this tool could be used for comprehensive assessments of crop yield, and to develop site-specific application maps for spray applications.

3. Field studies of robotic weed control systems

To date, only a few complete robotic weed control systems have been tested under field conditions. As this review shows, each of the core technologies for robotic weed control has required significant research and development efforts. Vibration, dust and other issues associated with implementing a real-time machine vision system on a mobile platform must be overcome. Once field testable solutions for each task have been developed they need to be integrated so that they perform correctly as a complete system, successfully passing information between subsystems and are correctly synchronized in order to actually kill the weed detected from a mobile platform. The integration task can be a significant effort of its own. The field performance of three robotic weed control systems will be reviewed.

Åstrand and Baerveldt (2002, 2004, 2005b) developed and tested an autonomous robotic weed control system for sugar beets. The system incorporated a machine vision guidance system, a second machine vision system for within row weed identification, and a selective rotary hoe for weed removal. The robot was able to follow the row by itself and to selectively remove weeds in the seedline between sugar beet plants. They investigated a sensor fusion approach, combining spatial context (plant spacing) with plant shape and color features to improve recognition rates. They found that, for direct-seeded situations, combining spatial context with plant shape and color made the system more robust to variations in plant appearance and type of weed species, but only when crop emergence rates were high and weed densities were low or moderate. A field test of the robotic weed control system was conducted in an organic sugar beet field at the first true leaf stage. Test results show that 99% of the sugar beets were not removed and 41–53% of the weeds were removed by the robot. Of the weeds not removed, 31% were adjacent (i.e. too close) to crop plants and 18% were growing in a location where a sugar beet seed did not germinate.

Blasco et al. (2002) developed a robotic weed control system for transplanted lettuce. The robotic end-effector killed weeds by using a 15 kV electrical discharge. Two machine vision systems were used, one to detect weeds in field images and a second to provide trajectory information for the end-effector when positioning the electrical probe to kill weeds. The system identified weeds by size (blobs much smaller then crop plants), ignoring weeds touching lettuce plants. In a field test, the machine vision system was able to correctly detect 84% of the weeds and 99% of the lettuce plants, requiring 482 ms/image.

Lamm et al. (2002) developed real-time robotic weed control system and tested it in commercial cotton fields. The robotic weed control system was capable of distinguishing grass-like weeds from cotton plants, and applying a chemical spray only to targeted weeds while traveling at a continuous speed of 0.45 m/s. The system used a unique machine vision algorithm that was very robust to occlusion based upon mathematical morphology to determine the diameter of the inscribed circle of a leaf for plant species recognition. In field tests in 14 commercial cotton fields, the system correctly sprayed 88.8% of the weeds while correctly identifying and not spraying 78.7% of the cotton plants while traveling at 0.45 m/s.

4. Summary

This review has summarized the current status of the four core technologies (guidance, detection and identification, precision in-row weed control, and mapping) required for the development of a general-purpose robotic weed control system for commercial agriculture. Three of the four technologies (guidance, precision in-row weed control, and mapping) have achieved a high level of development and some commercial success in non-robotic agricultural applications. The fourth, robust weed detection and identification, remains as the primary obstacle toward commercial development and industry acceptance of robotic weed control technology.

Both machine vision and RTK GPS guidance systems for precise position control of between-row mechanical cultivators are commercially available. These systems have similar levels of positioning precision along straight rows (generally in the 25 mm standard error range) and distinct advantages and disadvantages. Machine vision guidance systems require a reasonable view of a preexisting guidance directrix (typically the crop row), while RTK GPS systems require a good "view" of the sky and an RTK GPS base station located nearby and can be used for initial tillage tasks. Currently, equipment costs for machine vision guidance systems are considerably lower than RTK GPS equipment costs. Additional research is needed to fully document the performance of these technologies under a wider range of agricultural conditions.

Four types of weed control technologies (mechanical, thermal, chemical, and electrical), originally developed in the 1960s for automatic thinners, are suitable for selective in-row weed control by robotic systems. Three of the technologies (mechanical, thermal, and chemical) have been developed into successful commercial products for applications like thinning or between-row weed control. Some, like flaming and chemical applications don't require contact between the equipment and the weed and do not disturb the soil. Recent work on precision targeting of chemical spray has demonstrated the ability to target weeds within 1 cm of crop plants.

GPS technology and GIS software methods are widely available commercially and have been used by weed scientists in the manual development of georeferenced maps of weed distributions in agricultural fields. When integrated with machine vision weed sensing technology, they allow the automation of this valuable management tool.

A considerable amount of research has been conducted on various machine vision techniques for weed detection and identification. Most studies have been conducted under ideal conditions with no occlusion between crop and weed plants. Crop versus weed or individual species classification accuracies in the range of 65–95% are frequently reported under ideal conditions. The most common source of error cited is occlusion followed by poor plant segmentation if natural illumination is used. Most of the machine vision techniques investigated are not suited for real world conditions where weed and crop plants frequently occlude one another and leaf appearance is distorted by wind, insect or weather damage, water or nutrient stress, or shadows. Accurate and robust methods of automatic weed detection and identification are needed. The lack of robust weed sensing technology is the main limitation to the commercial development of a robotic weed control system.

Despite these challenges, there have been a few complete robotic weed control systems demonstrated in agricultural fields under a limited range of conditions. These systems demonstrate the promise of robotic weed control technology for reducing the hand labor or pesticide application requirements of existing weed control methods. Additional research is needed to fully optimize the technology for the wide range of conditions found in commercial agriculture worldwide.

Disclaimer of endorsement

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