AG 30. MACHINE VISION-BASED WEED SPOT SPRAYING: A REVIEW AND WHERE NEXT FOR SUGARCANE?

By:
CHERYL MCCARTHY[1], STEVEN REES[1], CRAIG BAILLIE[1]

[1]*National Centre for Engineering in Agriculture, University of Southern Queensland, Toowoomba.*
Cheryl.McCarthy@usq.edu.au

Keywords: Machine vision, image analysis, Guinea Grass, weed identification, precision agriculture

Abstract

Automated precision weed spot spraying in the sugarcane industry has potential to increase production while reducing herbicide usage. However, commercially-available technologies based on sensing of weed optical properties are typically restricted to detecting weeds on a soil background (i.e. detection of green on brown) and are not suited to detecting weeds amongst a growing crop. Machine vision and image analysis technology potentially enables leaf colour, shape and texture to achieve discrimination between vegetation species.

The National Centre for Engineering in Agriculture (NCEA) has developed a machine vision-based weed spot spraying demonstration unit to target the weed *Panicum* spp. (Guinea Grass) in a sugarcane crop, which requires discrimination of a green grass weed from a green grass crop. The system operated effectively at night time for mature Guinea Grass but further work is required for the system to operate under a greater range of conditions (e.g. different times of day and crop growth stages). Techniques such as multispectral imaging and shape analysis may potentially be required to achieve more robust weed identification. The implications for machine vision detection of Guinea Grass and other weed species in sugarcane crops are considered.

Introduction

Competition from weeds in sugarcane crops can significantly reduce yield (Hogarth and Allsopp, 2000) and potentially reduce the length of the crop cycle (i.e. the number of ratoons). Automated, targeted spraying of weeds offers the industry a number of economic and environmental advantages.

Commercially-available technologies typically involve identification of green from brown (i.e. vegetation from soil background) and may have simple leaf shape and size discrimination such as small/large or broadleaf/grass. These applications require that individual leaves be isolated and that weed and crop plants not be touching. Hence, the developed systems are suited to identifying weeds in fallow fields or pre-emergence and early-stage crops. The research literature reports a number of developments for the purpose of overcome such limitations. This paper reviews automated weed detection methods in commercial products and research prototypes, discusses their capabilities and highlights the limitations of machine vision weed identification.

The National Centre for Engineering in Agriculture (NCEA) has developed a weed spot spraying demonstration unit which was effective at identifying mature *Panicum* spp. (Guinea Grass) in a sugarcane crop at night time (Rees *et al.*, 2009). This entailed design of a machine vision system that could identify a green grass weed from a green grass crop. This paper is divided into two parts: the first provides a review of existing weed spot spraying technologies (commercially-available and image analysis technologies); and the second is a description of the machine vision-based weed spot spraying demonstration unit developed by NCEA.

Commercially-available technologies

One of the first commercial systems to be developed was the Weed Activated Spraying Process (WASP, later renamed to Detectspray) by Felton *et al.* (1987) at the NSW Department of Agriculture. The system was limited by its dependence on ambient lighting because it did not provide active illumination and no longer appears to be commercially available (Rizzardi 2007). Currently there are three main technologies commercially available for weed spot spraying which are:

- Photonic Detection Systems Pty Ltd (formerly Weed Control Australia);
- Weedseeker (formerly Patchen); and
- Rees Equipment.

Photonic Detection Systems Pty Ltd

A spot spraying system developed by Weed Control Australia (now Photonic Detection Systems Pty Ltd) assessed the spectral differences between weeds and the bare ground. Vegetation has a high reflectance in the near infrared wavebands whereas soil has a relatively low near infrared reflectance (Gibson and Power, 2000). The product discriminated different plant sizes and included a light source under a shade structure which improved accuracy. Photonic Detection System Pty Ltd have since developed a prototype which measures reflectance at three wavelengths using laser diodes and a line scan image sensor for intended use to discriminate vegetation species (Paap *et al.*, 2008).

Weedseeker

Similar to the product by Weed Control Australia, Weedseeker assesses the ratios of red and near infrared reflectances of vegetation and background (NTech, 2009). The Weedseeker features light emitting diodes (LEDs) to reduce dependence on sunlight and improve accuracy.

Rees Equipment

Rees Equipment developed a system that identified weeds based on colour and basic shape and size properties using video image analysis (Rees *et al.*, 1999). The vegetation was identified as weed and sprayed if the detected colour and shape matched an operator-defined prescription. The product was designed to spray weeds in a fallow situation and hence, had limited applicability to cropped areas. The system used a hood and artificial light source.

Commercially available technologies – summary

The Weed Control Australia, Weedseeker and Rees Equipment technologies were reported to be successful in discriminating between the ground and weeds. However, in practice the technologies are not suitable for a weed-in-crop environment as is required for the identification of weeds in a sugarcane crop. The prototype developed by Photonic Detection Systems Pty Ltd has intended use for species discrimination. A sensing strategy is required which incorporates a combination of vegetation properties including shape, spectral reflectance and texture to enhance weed and crop discrimination.

Image analysis

Site-specific herbicide application may be achieved in a weed-within-crop situation by automatic identification of weeds, crop or both. Publicly-reported literature includes discrimination of crop and weed species using shape (e.g. Lamm *et al.* (2002)), spectral (e.g. Wang *et al.* (2001)) and texture (e.g. Tian *et al.* (1999)) properties of vegetation. This may require an initial step of identifying vegetation from a background of soil or stubble. Reliable real-time sensing is required so that weed identification and an appropriate control action can be achieved from a moving agricultural vehicle. The ability of humans to identify different weed species by visual assessment suggests that an automated sensing system based on vegetation visual properties is feasible.

Ground-based and remote sensing platforms are possible for detection of weed spectral properties. Remote sensing platforms include balloon, aircraft and satellite. Weedy patches are expected to grow in thick patches in-field and have a stronger spectral reading compared to less-dense crop areas

(Thorp and Tian, 2004). However, the timeliness of remote sensing images reduces their practicality for day-to-day farm operations (Barnes *et al.*, 1996). Therefore, ground-based sensing of weeds is necessary for real-time weed sensing and control. Point (e.g. photo sensors) and imaging (e.g. cameras) sensors may potentially be used to detect weeds based on visual properties of vegetation.

Imaging sensors collect colour or intensity data about a scene in two dimensions. This potentially enables leaf shapes within the scene to be identified and analysed using automated image analysis techniques. Standard colour digital cameras sense reflectances in three wavebands (red, green and blue, also represented as *R*, *G* and *B*, respectively). However, the image sensors in standard consumer cameras have spectral sensitivity that extends into the near infrared range, which is a region of high reflectance for vegetation (Kumar *et al.*, 2001).

Segmentation of vegetation from background

A common first step in image analysis for weed identification is the segmentation of vegetation from the background. In outdoor field environments, sunlight conditions vary from overcast to sunny and at potentially short time intervals. This affects the relative contrast between the vegetation and background and the amount of shadows apparent in images (Ewing and Horton, 1999). There is often a range of colour intensities shared between objects and background that prevents the effectiveness of a monochrome threshold in outdoor images (Tian and Slaughter, 1998). Tian and Slaughter (1998) developed a learning algorithm to segment vegetation from background soil in daylight ranging from cloudy to sunny. The algorithm had improved performance compared with a static segmentation technique. Woebbecke *et al.* (1995) evaluated a range of red, green and blue ratios for segmentation and found that the excess green criterion ($2*G–R–B$) was most effective for detecting vegetation. Gerhards and Oebel (2006) successfully achieved segmentation of vegetation from soil using near infrared–visible difference images.

Segmentation algorithms may potentially be simplified by providing a controlled lighting environment for the outdoor vision system, as demonstrated by the commercially-available technologies. This may potentially be achieved by enclosing the camera and an artificial light source in a shroud that extends to the ground level, encompassing the vegetation of interest and excluding ambient daylight. A shroud composed of rubber flaps was used by Lee *et al.* (1999) and Astrand and Baerveldt (2002) to allow continuous within-crop movement of the enclosed vision system with artificial lighting.

Species classification based on leaf shape

Weeds and crop may be discriminated by leaf shape and size differences (e.g. between broad-leaf and grass species). Image analysis applications for leaf identification typically feature images with distinct shapes representing individual leaves. This occurs when the plants of interest are not touching due to their small size and dispersed spacing. Leaf shape properties may be extracted from images using shape operators (Lamm *et al.*, 2002) and frequency-domain analysis of leaf edges (Gerhards and Christensen, 2003). Species identification is achieved by classification of extracted shape parameters (e.g. elongation and compactness) with learning algorithms (e.g. Lee *et al.*, 1999; Gerhards and Christensen, 2003). Classification performance may be affected by leaves that are curled, occluded or insect damaged (Lee *et al.*, 1999).

Species classification based on spectral/colour differences

Colour differences between crop and weeds may be used to discriminate species. El-Faki *et al.* (2000) detected the red hues present in foxtail weeds to distinguish weed areas from crop. Five wavelengths in the visible spectrum were found to be useful for classifying weeds, wheat and bare soil under controlled lighting conditions (Wang *et al.*, 2001). However, Du *et al.* (2007) identified that environmental factors caused classification based only on leaf colour to be of low reliability.

Crop row geometry may be used in conjunction with colour analysis to identify weeds. Crops are expected to occur along the seed-row whereas weeds may occur both along the seed-row and between crop rows. In an application developed by Tangwongkit *et al.* (2006), any vegetation (green pixels) that occurred between rows was classified as weeds. The intensity of the green reflectance determined the amount of herbicide applied.

Species classification based on texture

Texture is a distinct pattern in reflected light and is caused by variations in crop colour and architecture in vegetation (Tian *et al.*, 1999). Texture analysis of plant top views permitted plant identification by image texture properties such as homogeneity, structuredness and brightness (Shearer and Holmes, 1990). Burks *et al.* (2000) developed a classifier to calculate 11 texture features of broad-leaf and grass weed species. Tian *et al.* (1999) evaluated a weed-sensing algorithm which used local image texture information to discriminate fine-blade grass weeds from larger-leaf corn plants at a continuous travel speed of 4.2 km/h. Texture analysis may be applied to images of canopies or individual leaves. Hence, texture analysis may potentially be used to discriminate more developed vegetation.

Image analysis for weed identification – summary

Segmentation of vegetation from the background in variable outdoor lighting conditions is a necessary preprocessing step. However, this step may be simplified using a controlled lighting environment and/or multiple-waveband imaging (e.g. a combination of visible and near infrared reflectances). Colour properties may be used in situations where there are distinct colour differences between the species required for classification. Discrimination between grass and broad-leaf species may be achieved using leaf shape properties such as compactness and elongation. However, in sugarcane, grass weeds are required to be identified in a thin-leaf crop environment. Therefore, a combination of crop texture, shape and colour properties is expected to be required to achieve successful discrimination between species. An NCEA weed spot spraying demonstration unit developed using these principles is described in the next section.

NCEA demonstration unit

The rest of this paper describes an NCEA demonstration unit which identified Guinea Grass in sugarcane crops using image analysis methods. SRDC funded NCEA to develop a machine vision system that could identify sugarcane from grass weeds of similar appearance. Initial investigations consisted of collecting video data which provided spatial (i.e. shape) as well as spectral information about the weeds and crop. In-field observations and inspection of video collected at different crop growth stages enabled visual differences between the leaf shape, plant structure and growth pattern of weeds and crop to be identified. Within any particular scene of a weed-infested sugarcane crop, there were readily identifiable morphological differences between species which enabled visual discernment of weeds and crop at all evaluated crop stages.

NCEA's weed spot spraying demonstration unit consisted of a camera, laptop computer with image analysis software and solenoid-activated spray nozzles (Rees *et al.*, 2009). The algorithm for weed detection consisted of the perceived colour difference between sugarcane and Guinea Grass, i.e. that sugarcane appeared "bluer" in colour than Guinea Grass. Additionally, algorithms were implemented that discerned the denser clumps of leaf blades characteristic of Guinea Grass, as opposed to the sparser spacing of sugarcane leaf blades.

Evaluation of image analysis performance on video collected in the field revealed that accurate algorithm results during the day required frequent manual recalibration of weed and crop colour due to variations in sunlight (see threshold values reported in Table 1), which is not feasible for routine or autonomous use. Subsequent night time trials (Figure 1) reduced the need for recalibration due to the constant outdoor lighting conditions. Successful image analysis detection (>90%) was achieved of Guinea Grass from mature sugarcane, based on comparison of manual observation and image analysis results for weed positions in collected video (Rees *et al.*, 2009).

Table 1. Typical results of the algorithm on the daytime video (Rees *et al.*, 2009).

Video no.	*Weed Threshold*	*Colour Threshold*	*Texture Threshold*	Hit	False negative (=100% – HIT)	False positive
1	0.199	244	118	100%	0%	1 trigger
2	0.231	227	95	100%	0%	2 triggers
3	0.213	236	108	92%	8%	1 trigger
4	0.198	241	114	100%	0%	0 triggers
5	0.179	242	115	100%	0%	0 triggers

Figure 1. Lighting apparatus for night time trials: (a) equipment setup indicating positions of camera (middle ellipse) and lights (outer two ellipses); and (b) sample image captured at night time (rendered in greyscale).

Analysis of image histograms of the blue intensities of sugarcane and Guinea Grass (Figure 2) revealed that on average they have different colours. Therefore, the difference as perceived by a standard RGB camera only occurs on average which means that a pixel captured in the range of intensities common to both Guinea Grass and sugarcane (i.e. the region of overlap in the histograms in Figure 2) may not be accurately assigned to either group. Hence, a narrowband imaging system which targets a discriminatory wavelength may potentially be a more robust detection method. This involves conducting a spectral analysis of the weeds required to be detected. It is anticipated that imaging in near infrared and visible wavelengths will enable robust soil segmentation and species discrimination. Implementation of a multispectral imaging system may potentially involve cameras installed with optical bandpass filters or a multiple-wavelength illumination scheme.

Conclusions

Weed detection algorithms require consideration of shape, spectral and/or texture properties of vegetation in controlled lighting to achieve robust species discrimination in a scene containing adjacent weeds and crop. The NCEA demonstration unit used algorithms based on colour and texture properties and achieved successful discrimination (>90%) of Guinea Grass from mature sugarcane. However, night time operation was required to increase calibration stability. Routine use of the system requires the design to be further developed for operation for different times of day, and be used for a variety of weed species and crop growth stages. Multispectral imaging is expected to be necessary to enable extension of the system to these conditions.

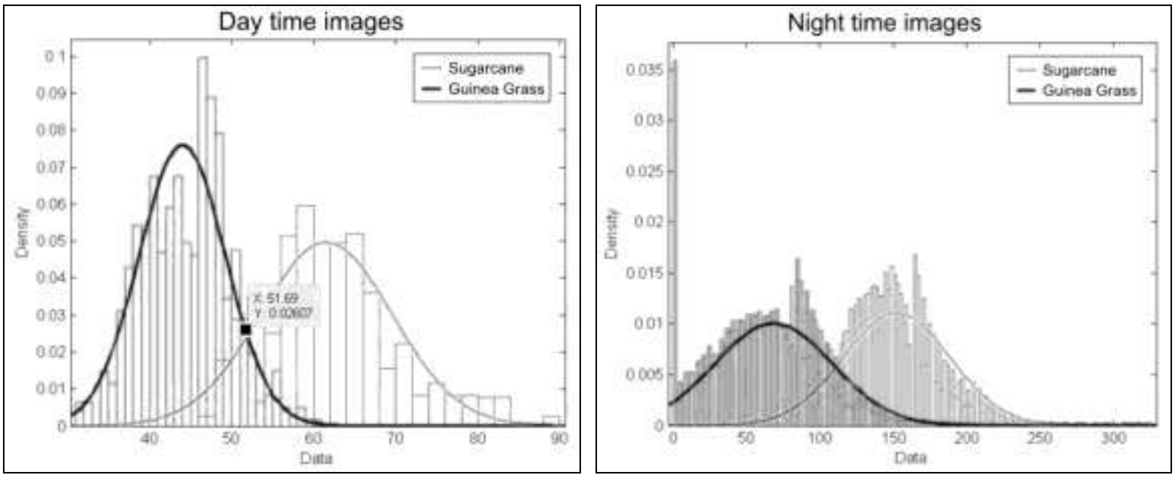

Figure 2. Intensity histograms for blue channel of sugarcane and weed images at day (left) and night (right).

Acknowledgements

The authors would like to thank SRDC for financial support and Bundaberg Sugar for field trial support throughout the project.

REFERENCES

Astrand B, Baerveldt, AJ (2002) An agricultural mobile robot with vision-based perception for mechanical weed control. *Autonomous Robots* **13**, 21-35.

Barnes EM, Clarke TR, Moran MS, Pinter PJ (1996) Multispectral remote sensing and site specific agriculture: examples of current technology and future possibilities. *Proceedings of 3rd International Conference on Precision Agriculture*, Minneapolis, Minnesota, pp. 843-854.

Burks TF, Shearer SA, Payne FA (2000) Classification of weed species using color texture features and discriminant analysis. *Transactions of the ASAE* **43**, 441-448.

Du J, Wang X, Zhang, G (2007) Leaf shape based plant species recognition. *Applied Mathematics and Computation* **185**, 883-893.

El-Faki MS, Zhang N, Peterson DE (2000) Weed detection using color machine vision. *Transactions of the ASAE* **43**, 1969-1978.

Ewing R, Horton R (1999) Quantitative color image analysis of agronomic images. *Agronomy Journal* **91**, 148-153.

Felton WL, McCloy KR, Doss AF, Burger AF (1987) Evaluation of a weed detector. In: Lemerle D, Leys AR (eds.) *Proceedings of the Eighth Australian Weeds Conference*, 21-25 September, Sydney, pp. 80-84.

Gerhards R, Christensen S (2003) Real-time weed detection, decision making and patch spraying in maize, sugarbeet, winter wheat and winter barley. *Weed Research* **43**, 385-392.

Gerhards R, Oebel H (2006) Practical experiences with a system for site-specific weed control in arable crops using real-time image analysis and GPS-controlled patch spraying. *Weed Research* **46**, 185-193.

Gibson P, Power C (2000) Introductory Remote Sensing: Digital Image Processing and Applications. Routledge, London.

Hogarth M, Allsopp P (eds.) (2000) Manual of cane growing. Bureau of Sugar Experiment Stations, Indooroopilly, Australia.

Kumar L, Schmidt KS, Dury S, Skidmore AK (2001) Imaging spectrometry and vegetation science. In: van de Meer F, de Jong SM (eds.) *Imaging Spectrometry*, Kluwer Academic Press, Dordrecht, pp. 111-115.

Lamm RD, Slaughter DC, Giles DK (2002) Precision weed control system for cotton. *Transactions of the ASAE* **45**, 231-238.

Lee WS, Slaughter DC, Giles DK (1999) Robotic weed control system for tomatoes. *Precision Agriculture* **1**, 95-113.

NTech (2009) “Weedseeker® Automatic Spot Spray System” Retrieved 11 February, 2010 from www.ntechindustries.com

Paap A, Askraba S, Alameh K, Rowe J (2008) Evaluation of an optical image sensor for use in the microphotonic real-time vegetation discrimination system. *Opto-Electronics and Communications Conference and Australian Conference on Optical Fibre Technology*. 7-10 July, Sydney.

Rees SJ, Rees JI, Kinmont AM (1999) Controller for agricultural sprayers. United States Patent 5924239, published 20 July 1999; expiry 24 April 2017.

Rees SJ, McCarthy CL, Artizzu XPB, Baillie CP, Dunn MT (2009) Development of a prototype precision spot spray system using image analysis and plant identification technology. *CIGR International Symposium of the Australian Society for Engineering in Agriculture.* 13-16 September, Brisbane.

Rizzardi K (2007) Site-specific weed management in peanut (*Arachis hypogaea* L.). University of Padua, Italy. Master's thesis.

Shearer S, Holmes R (1990) Plant identification using color co-occurrence matrices. *Transactions of the ASAE*, **33**, 2037-2044.

Tangwongkit R, Salokhe V, Jayasuriya H (2006) Development of a tractor mounted real-time variable rate herbicide applicator for sugarcane planting. *Agricultural Engineering International: the CIGR Ejournal* Manuscript PM 06 009, **3**.

Tian LF, Slaughter DC (1998) Environmentally adaptive segmentation algorithm for outdoor image segmentation. *Computers and Electronics in Agriculture* **21**, 153-168.

Tian LF, Reid JF, Hummel JW (1999) Development of a precision sprayer for site-specific weed management. *Transactions of the ASAE* **42**, 893-900.

Thorp KR, Tian LF (2004) A review on remote sensing of weeds in agriculture. *Precision Agriculture* **5**, 477-508.

Wang N, Zhang N, Dowell FE, Sun Y, Peterson DE (2001) Design of an optical weed sensor using plant spectral characteristics. *Transactions of the ASAE* **44**, 409-419.

Woebbecke D, Meyer G, von Bargen K, Mortensen D (1995) Color indices for weed identification under various soil, residue, and lighting conditions. *Transactions of the ASAE* **38**, 259-269.