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Weed detection for site-specific weed management: mapping and real-time approaches

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Summary

This work describes the current status of remote and proximal (on-ground) weed detection systems for site-specific weed management and discusses the limitations and opportunities of these technologies. Remote sensing based on multispectral aerial imagery can provide accurate weed maps, especially at late weed phenological stages, whereas images from high spatial resolution satellite and unmanned aerial vehicles must still be analysed. Hyperspectral images produce highly accurate maps at early and late phenological stages at a farm scale or medium spatial scale. However, this technology is not profitable, because of current operating costs, which are prohibitive. In studies of on-ground weed seedling detection, accurate results can be obtained at a medium farm scale. Despite numerous efforts, a powerful and flexible classifier of soil, weeds and crops in a number of situations, remains the greatest challenge of this technology. The main limitations of remote and proximal sensing may be summarised in the following two points: (i) the time and education required for applying new technological advances and (ii) the high cost of the technology and the lack of compatibility of the machinery. Possible solutions might include: (i) offering an advisory service that provides technical support, agronomic knowledge and specific training courses, (ii) the development and implementation of uniform and cheaper standards, (iii) increased research of both high resolution satellite imagery exploring object-based image analysis and pan-sharpened imagery and unmanned aerial vehicles (UAV) and (iv) enabling the development of current prototypes of robotic weeding into commercial products. The general lack of multidisciplinary research groups can be a disadvantage when comparing the economic feasibility of site-specific weed management with conventional systems.

Keywords: aerial and satellite imagery, hyperspectral, mapping weeds, multispectral, neural networks, precision agriculture, robotic real-time, remote sensing, spectral signatures, machine vision.

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Introduction

Site-specific weed management: general concepts

Site-specific weed management (SSWM) includes spraying weed patches only and/or adjusting herbicide applications according to weed density or weed species composition (e.g. herbicide resistant, broad-leaved or grass weeds). This strategy fits well with European goals of minimising herbicide use and tracing farm products (FP7-NMP, 2009). In many parts of Europe, field sizes are increasing, farmers frequently have a university degree and usually manage several fields (sometimes more than 3000 ha in southern Spain). These factors favour the adoption of precision agriculture, because the investments in technology and human skills can produce a faster and more positive return (Reichardt & Jürgens, 2009). SSWM represents a four-step cyclical process

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that includes (i) weed monitoring consisting of ground sampling or detection of weeds, (ii) decision-making (also called management planning), referring to the design of an action based on the diagnosis and other available information (e.g. previous farmer experience), (iii) precision field operation, which is the execution of SSWM and (iv) evaluation of the economic profitability, safety and environmental impacts of the field operations for the next season. Weed monitoring in crops is still one of the critical components for the adoption of SSWM. Large research efforts have been focused on this step, which is a prerequisite for both map-based and real-time-based weed monitoring.

Weed monitoring: general concepts

This article aims to review recent advances in monitoring of arable (in crop) weeds for SSWM (mainly for herbicide control) by considering remote (airborne-, satellite- and unmanned-based platforms) and proximal (ground-based sensors and cameras) sensing. The focus will also be on the opportunities and limitations of the application of this technology and on the need for future investigations into increase the acceptance and adoption of SSWM.

Site-specific weed management with a map-based approach consists of developing robust methods for weed data acquisition, analysis and delineation of management zones for further use. The spatial distribution of weeds within a crop can be detected and mapped by using remote sensing, which includes aerial and satellite imagery. It can also be detected by proximal sensing (Srinivasan, 2006), which refers to in-field machine-mounted (harvesters, tractors, robots) sensors. In contrast, real-time monitoring and spraying consists of a weed control system that can simultaneously detect and control weeds. This strategy requires monitoring processing techniques, decision-making and spraying while the vehicle is moving forward at a constant speed (e.g. Lee *et al.*, 1999). Therefore, remote sensing is helpful for map-based SSWM, whereas proximal sensing is useful for both.

Remote sensing

The spectral response of plant species at the canopy or single-leaf scale is unique and is known as spectral signature. One of its defining characteristics is that it varies according to the phenological stage and it can be measured by proximal or remote sensors (Peña-Barragán *et al.*, 2006; López-Granados *et al.*, 2008). The basic principle is that if differences in reflectivity based on external factors or distinctive phenological stages can be measured or recognised, there is potential for automatic weed detection or mapping (monitoring). Multispectral broadband sensors usually collect data for 3–7 bands of around 100 nm width, whereas hyperspectral sensors detect many narrow and contiguous wavelengths, usually <10 nm width (Table 1). Thus, as bandwidths are narrower in hyperspectral scanner systems, small variations in reflectivity can be detected that might otherwise be masked within the broader bands of multispectral scanner systems.

Together with the importance of spectral resolution, the other essential parameter in remote sensing is to select the suitable pixel size, based on the inherent properties of the input data, i.e. what is the smallest discernable feature at any given spatial resolution and the accuracy at which it is mapped. Hengl (2006) discussed the rules of thumb to find the right pixel size to help inexperienced users select the appropriate spatial resolution. He concluded that at least four pixels are required to detect smallest objects and at least two pixels to represent the narrowest objects, being objects the smallest size area that we map (weed plants or weed patches in our case). In other words, if the smallest object is a weed patch of 16 m^2 (4×4 m), we should use imagery with resolution of 2 m and finer. In Table 1 are shown some of the current multispectral and hyperspectral sensors, with the appropriate spatial resolution to detect and map weeds for SSWM. In the following sections, the detection of seedling or mature weeds based on the use of imagery with different spectral and spatial resolutions is presented.

Early (seedling) weed detection

In most weed control situations including SSWM, it is generally necessary to control weeds at an early growth stage of the crop. However, remote sensing of grass weed seedlings in monocotyledonous crops and seedlings of broad-leaved weeds in dicotyledonous crops presents much greater difficulties than mapping them in the late stage, for three main reasons: (i) cereal crops and grass weeds (and also many dicotyledonous crops and broad-leaved weeds) generally have similar reflectance characteristics early in the season, which could involve the necessity of using hyperspectral data to detect small variations in reflectivity, (ii) the distribution of weeds can be in small patches, which could indicate the necessity to work with very high spatial resolution imagery and (iii) the soil background reflectance interferes with detection (Thorp & Tian, 2004).

The next point is to determine whether the criterion for SSWM might be the presence or absence of weeds, or differentiation into monocotyledonous or dicotyledonous groups without any differentiation of weed species, as these weed groups are treated with different herbicides

Table 1 Some of the current sensors and platforms with spatial and spectral resolutions required for site-specific weed management

Sensors and platforms	Spatial resolution (m)	Waveband interval (nm)	Altitude (km)	Revisit time (days)
Multispectral satellite				
IKONOS	4*	450–900†	681	1.5
QuickBird	2.44*	450–900†	450	1–3.5
GeoEye-1 (former OrbView5)	1.64*	450–920‡	681	2.1–2.8
Airborne				
Daedalus 1268	3.44§	420–13000¶	1.37	
Conventional turboprop	0.30	400–900**	1.52	
Twin-engine plane				
Unmanned aerial vehicle (UAV)	0.15§	490; 530; 570; 670; 700; 750; 800††	0.15	
Hyperspectral airborne				
AVNIR#	1	430–1012 (10 nm)	1.5	
CASI	1–3§	400–1000 (1.9 nm)	0.84–3.5	
AHS	2–3.44§	430–12500 (13–300 nm)	1–1.37	
HyMap	2	450–2500 (20–10 nm)	2	
AVIRIS	4	400–2500 (10 nm)	3.8	

*1, 0.61, and 0.5 m spatial resolution in Panchromatic for IKONOS, QuickBird and GeoEye respectively.

†Bands: Blue, 450–520; Green, 520–600; Red, 630–690; Near-infrared, 760–900.

‡Bands: Blue, 450–510; Green, 510–580; Red, 650–690; Near-infrared, 780–920.

§Spatial resolution depends on flight altitude and camera field of view (FOV). Some examples as follows: angular FOV of 85.92° and 1.376 km flight altitude yield 3.44 m pixel for Daedalus and AHS; angular FOV of 42.8° × 34.7° and 0.150 km flight altitude generate 0.15 m pixel size for UAV; angular FOV of 60° and 2 km flight altitude yield 2 m pixel for Hymap. For Hyperspectral imagery, pixel size can also depends on the program to capture the image: for example CASI can offer submetre (0.7 m) pixel when only several wavebands (e.g. 18 wavelengths rather than the 288 available) are selected.

¶Fixed channels of Daedalus 1268: 420–450; 450–520; 520–600; 600–620; 630–690; 690–750; 760–900; 910–1050; 1550–1750; 2080–2350; 8500–13000.

**Bands: Blue, 400–500; Green, 500–600; Red, 600–700; Near-Infrared, 700–900.

††These channel centres are just an example because different bandsets can be selected depending on the objectives adopted for the UAV study.

#AVNIR, Airborne Visible and Near-Infrared; CASI, Compact Airborne Spectrographic Imager; AHS, Airborne Hyperspectral Scanner; AVIRIS, Airborne Visible/Infrared Imaging Spectrometer.

and usually have different spectral characteristics. There are only a few reports on the ability of airborne multispectral imagery to create accurate weed seedling maps in crops for in-season site-specific post-emergence herbicides. Brown and Steckler (1995) discriminated several broad-leaved and grass weeds in early-stage no-tillage maize (*Zea mays* L.) using 10-cm pixels. Lamb *et al*. (1999) mapped continuous *Avena* spp. populations in a seedling triticale crop using 0.5- to 2.0-m pixels. Medlin *et al*. (2000) discriminated seedlings of several weed species in early-season soyabeans (*Glycine max* L.) with 1-m spatial resolution. These works concluded that further investigations should evaluate the accuracy of weed detection with high spatial resolution imagery (pixels of at least < 0.5 m). Gray *et al*. (2008) discussed the accuracy of weed seedling maps representing bare soil, soyabean and six weed species grouped. They also examined the accuracy for bare soil, soyabean and all weed species independently, using aerial images with 50-cm pixels taken 8 and 10 weeks after emergence. They reported that the accuracy was higher when remote sensing data were obtained 8 weeks after emergence and that the differentiation of each weed species would require hyperspectral airborne imagery and a more powerful image analysis technique than the maximum-likelihood classifier. This imagery has the appropriate spectral resolution to detect weeds at the early stage. However, very little literature is available on the use of hyperspectral airborne imagery for weed detection during the early growth stages of a crop. Martín *et al*. (2009) mapped three weed seedling species (*Sorghum halepense* L., *Xanthium strumarium* L. and *Abutilon theophrasti* Medicus) in early maize using an Airborne Hyperspectral Scanner (AHS) with 80 wavelengths in the visible and near-infrared domains. Goel *et al*. (2003a,b) and Karimi *et al*. (2005) used CASI (Compact Airborne Spectral Imager) hyperspectral sensors with 72 narrow bands (also visible to near-infrared) to map grass weeds (*Cyperus esculentus* L., yellow nut sedge; *Echinochloa crus-galli* L. Beauv., barnyard grass; *Digitaria ischaemum* Schreb., crabgrass) and broad-leaved weeds (*Cirsium arvense* L. Scop., creeping or Canada thistle; *Sonchus oleraceus* L., sow thistle; *Amaranthus retroflexus* L., redroot pigweed; *Chenopodium album*, fat-hen, among others) in maize fields. Despite this research, the main restriction of hyperspectral remote sensing is that it is only cost-effective on a large scale, or if two objectives, such as site-specific herbicide and fertilisation applications, are solved in the same operation.

Currently, the multispectral satellites with higher spatial resolutions with potential for discriminating weed seedling in crops are QuickBird and GeoEye, with 2.44- and 1.64-m pixels in multispectral resolution respectively. QuickBird has provided accurate maps of *C. arvense* in sugar beet at the cotyledon stage (Backes & Jacobi, 2006), but no information has been found regarding the use of GeoEye imagery for mapping weeds in the early growth stages of crops.

Late (mature) weed detection

An alternative to early detection is late detection, because the differences in the weed-crop life cycle at advanced phenological stages may enhance spectral differences. Thus, detection of late-season weed infestation has considerable possibilities when the soil surface is completely covered, the weeds exceed the crop canopy, and the spectral differences between crops and weeds are present and are quantifiable. Because weed infestations can be relatively stable in location from year to year (Barroso *et al*., 2004; Heijting *et al*., 2007a; Jurado-Expósito *et al*., 2004, 2005), late-season weed detection maps can be used to design SSWM in subsequent years, to apply in-season post-emergence herbicides if adequate pre-emergence control was not achieved, or to know where the greatest weed seed rain and seedbanks are in the field (Koger *et al*., 2003). Post-emergence site-specific applications can be useful to control broad-leaved and grass weeds in maize (Brown & Steckler, 1995), to control cruciferous (e.g. *Sinapis* spp. and *Diplotaxis* spp., De Castro *et al*., 2009) or grass weeds (e.g. *Avena* spp.) with specific and very expensive herbicides in cereals, or to treat herbicide-resistant weeds such as ryegrass (*Lolium rigidum* Gaudin) (López-Granados *et al*., 2008). Thus, the discrimination of these problematic weeds at advanced phenological stages could justify the necessity in reducing herbicide use and cost, or of planning a specific application for herbicide-resistant weeds.

Conventional colour (400–700 nm) and colour-infrared (500–900 nm) films for aerial photography have been reported to accurately map late infestations of maize caraway (*Ridolfia segetum* Moris) in sunflower with 0.40-m pixels (Peña-Barragán *et al*., 2007). Gibson *et al*. (2004) used aerial multispectral digital images with 1.3-m pixels to map late infestations of weeds in soyabean while considering both the effects of weed density and weed species discrimination accuracy. They reported that classification accuracy decreased as weed density or cover decreased. This finding indicates that a greater spatial resolution is required to detect low weed densities and that weedy pixels (presence of weeds) were separated from weed-free and bare ground (absence of weeds) with maximum 11% error, whereas the classification error of weed species ranged from 17% to 39%. López-Granados *et al*. (2006), using greater spatial resolution aerial imagery (0.30-m pixel), reported a high accuracy (ranging from 85% and 90%) when no weed species were taken into account. However, they did not improve the weed species classification (accuracy < 75%) when discriminating between wild oat (*Avena sterilis* L.), canary grass (*Phalaris brachystachys* Link.) and *L. rigidum* in wheat. To overcome this limitation, the use of hyperspectral imagery or a more powerful image analysis algorithm than vegetation indices or Spectral Angle Mapper methods have been suggested to improve classification results. Gutiérrez-Peña *et al*. (2008) applied neural networks and improved the accuracy of previous *R. segetum* maps (Peña-Barragán *et al*., 2007) by up to 15%. No information has been found regarding the use of hyperspectral imagery for mapping late weeds in crops.

Recently, unmanned aerial vehicles (UAV), which are unpiloted aircraft guided by autonomous navigation systems, have been presented as a promising tool in several agricultural applications (Schmale *et al*., 2008). The development of UAV could have great potential to monitor early and late weeds for site-specific applications, because they can provide low-cost near-real-time approaches with high spatial, spectral and temporal resolutions and low-cost autopilot systems. However, at present, there is very little information about UAV and weeds. Herwitz *et al*. (2004) mapped guinea grass (*Panicum maximum* Jacq.) within coffee fields when the weeds were yellow-green and the coffee trees were darker-green. Göktoğan *et al*. (2010) have developed a rotary-wind UAV to survey infestations of two aquatic weeds (*Alternanthera philoxeroides* Mart.Griseb, alligatorweed; and *Salvinia molesta* Mitchell, salvinia, giant). Information on UAVs and weeds is scarce, particularly for arable cropping.

Commission vs. omission errors

The agronomic implications of underestimation and overestimation of weed pressure is usually addressed through studying the risk of omission and commission errors. Omission error indicates the proportion of true weedy pixels not identified in the detection method and thus contributes to underestimation of the weed patches. Commission error indicates the proportion of pixels misclassified as weedy, meaning that the classification overestimates the weed patches and therefore provides a conservative estimation. From an agronomic point of view, it is more desirable to select a classification in which the omission error tends to be lower and the commission tends to be higher so that the weed patches are less likely to be missed. Gibson *et al.* (2004), Lamb and Weedon (1998) and Peña-Barragán *et al.* (2007) obtained less omission than commission errors in their weed detection studies in soyabean, oilseed rape stubble and sunflower with multispectral aerial imagery.

Limitations and opportunities of remote sensing

The most important findings of the previous sections regarding early or late detection by remote sensing are (i) the primary aim for detecting and mapping weeds at early or late phenological stages is the presence or absence of weeds and not the differentiation between individual weed species, (ii) this is achievable with acceptable accuracy with pixels around 0.5 m and visible and near-infrared multispectral windows, and (iii) weed discrimination decreases with poorer spatial resolution. To discriminate weed species, it is necessary to explore hyperspectral airborne data.

Moran *et al.* (1997), Lamb and Brown (2001) and Shaw (2005) reviewed the potential for image-based remote sensing to provide spatial and temporal information for SSWM. They concluded that the potential market for remote sensing products in precision management is good, focussing on the necessity of assimilating remotely sensed information into efficient decision support systems. The current challenge for SSWM with multispectral remote sensing is to check whether high spatial resolution images (pixel < 0.5 m) can accurately map weed seedling in crops for in-season, operational selective herbicide applications. This line of research can be complemented or overcome by mapping weeds at later phenological stages for the next season/s or for in-season post-emergence herbicide site-specific control. The development of low-cost autopilot systems, along with the availability of very small pixel size (e.g. 15 cm, Table 1) and a reduction in the weight and price of sensors that can be installed in the UAV, has meant that scientific interest in this kind of platform is growing for different site-specific agricultural applications. In the case of weed detection, there is a wide and promising area that requires research attention. The only price constraint on imagery acquirement is the size of the surveyed area.

Companies that distribute high spatial resolution satellite imagery usually offer users two separate products: a high spatial resolution panchromatic image (QuickBird, 0.7-m pixel; GeoEye, 0.5-m pixel) and a lower spatial resolution multispectral image in the visible and near-infrared spectral range (QuickBird, 2.44-m pixel; GeoEye, 1.64-m pixel), as well as average revisits of 1–3.5 and 2.1–2.8 days for both QuickBird and GeoEye imagery. The high spatial resolution of panchromatic images would have the potential to accurately map weed patches, and the high spectral resolution of multispectral images would facilitate the discrimination of weeds and crops. To obtain an image of high spectral and spatial resolutions, a pan-sharpening process or image fusion can be used to provide a pan-sharpened or single image that combines high spectral information (from multispectral imagery) and high spatial information from the panchromatic image. As a result, a 4-band multispectral pan-sharpened image with a spatial resolution of 0.7 or 0.5 m for QuickBird or GeoEye can be obtained. Castillejo-González *et al.* (2009) used a wavelet-based fusion technique in QuickBird imagery to improve the performance of several classification methods for precise monitoring of crops. The use of this fusion technique could be a potential solution to improve the accuracy of maps of early or late weeds in crops.

Another way to improve the accuracy of weed maps is to group adjacent pixels into spectrally and spatially homogeneous objects created via a segmentation process. Blaschke (2010) gives an overview of the development of object-based methods and suggests that the pixel paradigm is beginning to show cracks because of object-based methods represent a significant new trend in remote sensing for many monitoring programmes. The objects are not characterised by a uniform spectral value but by the distribution of a spatial autocorrelation. Thereafter, the classification is not based on pixels but on objects as the minimum information unit, as reported for QuickBird imagery (Castillejo-González *et al.*, 2009). Since a number of studies have shown the spatial correlation and patchiness of broad-leaved and grass weed species (Heijting *et al.*, 2007b; Jurado-Expósito *et al.*, 2009), the reasoning behind the segmentation process is quite straightforward: if weeds are distributed in patches, it is likely that the classification of objects consisting of similar adjacent pixels will improve the weed mapping, particularly if merely the presence or absence of weeds is the goal.

One of the keys for practical SSWM is to translate the detected weed pressure into management zones. To define such zones, three questions were raised (Fridgen *et al.*, 2004): (i) which information should be used (e.g. the economic threshold)? (ii) how is this information processed? and (iii) how many zones should be established within a field to make the management feasible for the farmer? Fuzzy clustering algorithms (Meyer *et al.*, 2004), development of software for automatic assessments of homogeneous areas (García-Torres *et al.*, 2008) and segmentation techniques (Costa *et al.*, 2007) have been applied to remotely sensed data to define less than three or four management zones, with satisfactory results for soil management (Khosla *et al*., 2007; Song *et al*., 2009) and for weed management in sunflower (Peña-Barragán *et al*., 2010) at the research level. However, it would be beneficial to develop further information for the delineation of management zones for herbicide application in a larger number of crops, to offer real solutions to farmers.

In conclusion, there are opportunities for using objects *vs* pixels as minimum information units for weed classification and mapping in remote sensing, and a cluster analysis (or other analysis) for delineating a restricted number of management zones. An additional task would be to assess the accuracy of zone maps based on QuickBird or GeoEye pan-sharpened imagery, which can offer solutions on large scales. Finally, airborne hyperspectral sensors have the desirable spatial resolution and mission flexibility for mapping seedling and mature weeds in crops, but operating costs and lack of companies that provide a cost-effective product make them unaffordable for farmers and consultants, at the moment.

Proximal sensing: mapping and real-time control

For site-specific control on finer spatial scales, there is interest in monitoring weeds using digital cameras, or spectral or optical sensor systems (non-imaging sensors) from ground-based platforms. Brown and Noble (2005) and Slaughter *et al*. (2008) reviewed the use of ground-based non-imaging sensors to identify crops, weeds and background soil. Non-imaging optoelectronic sensors have been developed by research groups (Dammer & Wartenberg, 2007; Wang *et al*., 2007) or are commercially available (e.g. WeedSeeker®, http://www.ntechindustries.com) for real-time spraying on cereals, pea or fallows and can be adapted for crops, such as vineyards and orchards. In these situations, all vegetation is assumed to be weeds and the only task is to discriminate between plants and soil. Thus, this review only includes research on automatic image processing systems.

High-resolution on-ground monitoring can be used in both map-based and real-time SSWM. Map-based involves two approaches: (i) an automatic weed detection system to input digital images and a subsequent computer-based image analysis to map the weed distribution and (ii) a real-time image analysis consisting of an automatic weed detection system mounted in the front of a tractor (or similar) analysing the images in real-time, but spraying later using the georeferenced map of weed distribution in a subsequent field operation. The first approach requires a digital camera and a differential global positioning system (DGPS), and the second one requires a digital camera, a computer-based image analysis with a plant identification algorithm and DGPS.

The real-time SSWM needs are for a vehicle to have sensing, decision-making and weed control implements for site-specific treatments. Real-time SSWM includes two approaches: (i) a weed detection-tractor-sprayer combination, in which variable spraying is applied according to weed detection in a single operation (usually used for extensive crops such as cereals) and (ii) a small autonomous vehicle that integrates detection and control of weeds also in a unique and simultaneous operation (robotic weeding) (usually used for high value crops such as tomatoes). The second approach would aim to replace traditional large tractors with small autonomous machines. The next sections will present the main findings of proximal sensing for both weed mapping and real-time SSWM.

On-ground image analysis for weed mapping

There are a number of concepts or parameters that are important in automatic image processing. Machine vision is the term that refers to the capture of on-ground images, and rule-based pattern recognition refers to the extraction of quantitative features (Guyer *et al*., 1993). Gerhards and Christensen (2003) and Gerhards and Oebel (2006) used differential images (NIR-visible) obtained with a set of three digital bi-spectral cameras mounted in the front of a sprayer at a speed of 5–8 km h^{-1} taking around 3000 images ha^{-1}. They analysed the images in real-time, identifying characteristic shape features of crop and weeds, but the spraying was conducted in a later field operation. They grouped weed species according to their sensitivity to herbicides and achieved a fast variation of herbicide mixture according to weed species distribution, reaching a reduction of herbicide from up to 20% to 90%, and from 5% to 81% for grass and broad-leaved weed herbicides in winter cereals and rape, maize and sugar beet. Sun *et al*. (2010) have developed an automatic, centimetre-level accuracy mapping system for real-time mapping of every plant of vegetable crops, such as tomato, during transplanting. The crop map generated is suitable for subsequent between-rows and within-row mechanical weed control.

Several ground-based systems, such as tripod (e.g. a digital camera at 0.45–0.50 m above the soil surface sampling continuous transects) Berge *et al*. (2008), and tractors (e.g. digital cameras at 1.7 m above the ground level) at a speed of 2.25 m s^{-1} (Hague *et al*., 2006) or 4 km h^{-1} (Tellaeche *et al*., 2008), have been tested for taking the digital RGB (red-green-blue) imagery for subsequent image classification. Eddy *et al.* (2008) used hyperspectral imagery acquired at ground level at 1 m target distance (1.25 mm pixel and 400–1000 nm spectral range at 10 nm intervals) and compared a new hybrid segmentation-artificial neural network method to a standard maximum-likelihood classification, for discrimination of redroot pigweed and wild oat in oilseed rape, pea and wheat, in both single date and multitemporal data. They discriminated weed species and crops with overall accuracies from 84% to 92% for multitemporal classifications and using the new algorithm, which implies improvements up to 31% over the standard weed control method.

At this point, it is essential to elucidate the importance of always using the same concept to compare different investigations. Thus, Burgos-Artizzu *et al.* (2009) attempted to clarify the controversy regarding the possible use of weed biomass, weed density, weed pressure (a visual estimate of the percentage that weeds contribute to the total volume of crops and weeds in a given area, considering the volume estimates as both height and surface area simultaneously covered by crop and weed), weed coverage, and the relative leaf area of weeds ('weed cover'), as some of the different parameters to be used in on-ground image analysis. They suggested that an image processing system that estimates the relative weed leaf area per image is much better adapted to machine vision than to the other weed abundance measures, because correlation coefficients with current data were 80%.

One of the on-ground automated image processing for crop and weeds detection has been the segmentation of images for object-oriented analysis by converting every (usually) RGB image to a binary black & white image. The first step is to obtain an image where white pixels represent vegetal cover (crops and weeds) and black ones the soil. In the second step, the zones corresponding to crops are identified and eliminated, and finally, the location of weeds is obtained (Burgos-Artizzu *et al.*, 2009). The leaf shape, colour and texture for each individual object in the image have been successfully used to distinguish several weed species and volunteer potatoes at the seedling stage in maize, soyabean, wheat and sugar beet (Guyer *et al.*, 1986, 1993; Zhang & Chaisattapagon, 1995; Nieuwenhuizen *et al.*, 2007). Tellaeche *et al.* (2008) reported the results of weed detection in maize through a two-step process: (i) image segmentation in cells of 8500 and 1660 pixels for cells in the bottom and upper part of the images because of the perspective of them, and (ii) a decision-making process to determine whether or not a cell is to be sprayed. The tractor speed was 4 km h^{-1}, which implied that 12 m was covered in 11 s. Other works have applied fuzzy logic algorithms and artificial neural network classifiers to discriminate young weed species in maize at the two- to five-leaf stage (Yang *et al.*, 2002) and sunflower at the four-leaf stage (Kavdir, 2004). They analysed hundreds of images and there could be enormous differences between images. These differences are the key to understanding the complexity of a robust analysis of every image, and they are directly related to the performance of the image analysis process. Therefore, a classifier of soil, weeds and crops has to be powerful and flexible in a number of field situations. Burgos-Artizzu *et al.* (2009) discriminated barley, soil, *A. sterilis* and *Papaver rhoeas* L. (poppy) in outdoor field images under varying light conditions, soil background texture and crop conditions over 4 years by means of a Case-Based Reasoning system.

Most of the research reviewed has concluded that subsequent investigations should address on-line weed identification for real-time herbicide application, which is the main issue addressed in the next section.

Decision-making and real-time robotic weed control

To date, very few complete real-time robotic site-specific weeders have been tested under field conditions. Lee *et al.* (1999) correctly identified 73% of the tomatoes and 69% of the weeds (thirteen species) testing their robot for real-time spraying of in-row grass and broad-leaved weeds. The prototype travelled at a speed of 1.2 km h^{-1}, with 58.10 and 37.44 ms for the execution time to find the tomato and weed locations, and to send tomato and weed locations to the spray controller respectively. Slaughter *et al.* (2008) reviewed real-time robotic weeding, including methods for improving the accuracy of detecting weeds under varying natural illumination conditions, as well as methods for mechanical, thermal, herbicide and electrical weed control in several crops. They concluded that vibrations, dust and other issues associated with real-time machine vision systems need to be overcome.

An additional challenge of SSWM weed control based on on-ground image analysis for weed mapping or for real-time is to determine the correct herbicide application rate according to the weed classification. Some authors have developed or applied decision support algorithms, such as WeedSOFT and Decision Algorithm for Patch Spraying (DAPS), to estimate the optimal herbicide rate. They introduced parameters such as relative competitiveness and the dose–response curves of several herbicides in field conditions (Christensen *et al.*, 2003; Neeser *et al.*, 2004; Rider *et al.*, 2006). More recently, Christensen *et al.* (2009) reviewed the current status of precision sprayers, including those with direct injection and Drop On Demand Application Systems. There are commercially available digital video cameras that view the crop ahead of the tractor for real-time spraying on different arable and horticultural crops (e.g. http://www.garford.com).

Limitations and opportunities of proximal sensing

On-ground image processing procedures can be considered similar for mapping and for real-time applications. The main difference is that in real-time robotic weeding, image analyses, decision-making and action mechanisms (actuators) to open the sprayers, adjust the herbicide rate, and control the actuation, must be conducted in one operation. The reactions of autonomous vehicles in changing contexts for real-time SSWM are highly dependent on the nature and reliability of the decision-making process and how this process is used. Because of the very short time between detection and action, the image or sensor processing time must be greatly reduced, necessitating the avoidance of computationally intensive steps. Similarly, the decision-making system must be fast, robust, flexible and simple. The main problems to solve are related to: (i) agronomic situations, e.g. each crop field presents enormous differences in weed species and abundance, and crop plants can be confused as or hidden by weeds, or *vice versa*, and (ii) automation technology, e.g. robots, must be successful for emergency stops, abrupt terrains or static (stones) and dynamic (animals) obstacles. The travel speed of the autonomous vehicle is also highly influential, because it must be cost-effective and it is directly related to the weed identification and position error of weed or patch detection. Although machine vision and real-time kinematic (RTK) GPS guidance systems for SSWM by between-rows mechanical cultivators are commercially available, additional research is needed to combine existing algorithms for herbicide spraying and to test the performance of these technologies under a wide range of agricultural situations.

Final comments: directions for further research

Fernández-Quintanilla *et al.* (2008) point out that interactions between weed science and robotic and information technologies are important, if we are to realise the potential herbicide savings that a spatial distribution of weeds offers. They also note that SSWM may provide an answer to new European regulations regarding pesticide use. Recent articles have reviewed a number of topics relevant to the adoption and future perspectives of SSWM: (i) the status of the farm (size, kind of crops), farmers (education, age, interest in new technologies) and lack of compatibility between machines (Reichardt & Jürgens, 2009), (ii) site-specific weed control technologies (Christensen *et al.*, 2009), (iii) SSWM with one or several herbicides (Wiles, 2009), and (iv) robotic weeding (Slaughter *et al.*, 2008). Most of the articles reviewed were not conducted by interdisciplinary groups. This can be disadvantageous when comparing the economic feasibility of site-specific weed management with conventional systems. To overcome the current problems, European research projects (FP7-KBBE, 2008; FP7-NMP, 2009) are raised to configure colonies of robots for real-time management decisions. This research expects to improve the current vision, suspension, guidance, energy (power) safety, decision-making and actuator systems. These projects are interdisciplinary and enterprises and experts from unrelated disciplines, such as agronomy (weed science), remote sensing, electronic engineering, computing, economy or physics, are collaborating. This interdisciplinary strategy is the key to achieving progress and to responding to the heterogeneous objectives that SSWM presents. Research needs encompass comparing the use of remote and proximal sensing in several crops to evaluate risks and benefits and to calculate the economic output that an enterprise can expect when investing in this technology. There should be an ambitious work plan that would allow testing of the potential success widely expected from SSWM.

Conclusions

Site-specific weed management includes a wide range of methods for the acquisition and analysis of information. Based on reviewed literature, the main limitations for operational SSWM can be summarised in four points: (i) the educational requirements of end-users for learning new technological advances and the lack of compatibility between current and new machinery and between machines from different manufacturers, (ii) the high cost of the technology, (iii) the use of remote sensing imagery that covers large-scale infestations to create timely (early or late) and accurate weed maps, and (iv) the use of robots that must usually work under a wide range of changing environments.

Possible solutions to these constraints might include the following: (i) the development and implementation of uniform and cheaper standards, which may occur if competition between companies increases, (ii) offering an advisory service that provides technical support, agronomic knowledge and specific training courses, (iii) more research on UAV and high resolution satellite imagery, and (iv) enabling the development of new prototypes or improving the current prototypes of robotic weeding into commercial products.

In conclusion, these major milestones could result in both an accurate and low-cost sensor for detecting or mapping weeds in an autonomous and safe robotic vehicle. This vehicle would have powerful decision-making capabilities and would be equipped with individual spray nozzles for SSWM and/or using high resolution satellite or UVA images in which a high performance algorithm could be incorporated into the image analysis for timely and accurate weed and crop mapping.

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