PR471
July 2010
£8.55

Project Report No. 471
Proof of concept of automated mapping of weeds in arable fields

by

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This is the final report of a 12 month project which started in April 2009.
The work was funded by a contract for £30,000 from HGCA (RD-2007-3402).
The project was co-funded as follows:

DEFRA (via HSE Chemical Regulation Directorate), £62692 cash;
Concurrent Solutions LLC, £12800 in kind;
Syngenta Crop Protection Limited, £8420 in kind;
Patchwork Technology Limited, £4040 in kind;
Herbiseed, £3000 in kind.

ACKNOWLEDGEMENTS

We gratefully acknowledge co-funding by the UK Government Department for Environment, Food and Rural Affairs (DEFRA via the Chemical Regulation Directorate), the Agriculture and Horticulture Development Board-HGCA (AHDB-HGCA) and in-kind contributions from Concurrent Solutions LLC, Syngenta Crop Protection Limited, Patchwork Technology Limited and Herbiseed.

Thanks are especially due to personnel from these organizations for support, encouragement and advice, without which the project could not have been carried out. These include Julie Howarth (UK Chemical Regulation Directorate); Dr David Cooper (DEFRA); Dr James Holmes (AHDB-HGCA); Jerry Edwards and Shane Sanford of Concurrent Solutions; Tom Robinson and Ben Magri (Syngenta Crop Protection); Nick Walters of Patchwork Technology; and Steve Morton of Herbiseed.

Academic support and expert advice from Professor Paul Miller (The Arable Group, Silsoe Spray Applications Unit) and Dr Peter Lutman have been much appreciated.

As with most projects, there are unsung heroes. At Reading, we particularly want to thank Mrs Caroline Hadley, Mr Richard Casebow and Mr Laurence Hansen for technical help. Caroline took the minutes at two project meetings and provided technical help. Richard quickly mounted the camera on a tractor and then drove it at manic speeds to enable us to capture images at different speeds and allowed us to plant black-grass and wild-oats on the university farm! Laurence husbanded black-grass and wild-oat seedlings for us. Tim Scott's fields near Cambridge were the focus of much of the research and sprayers, tractors and combines were driven over the fields to capture images. Special thanks are due to Simon Beddows of Phillimore Farms near Reading, who provided access to his fields and let us capture images while combine harvesting. We also thank Guy Hildred for providing access to capture images on Icknield Farm.

We are grateful to others who have provided administrative support at Reading, especially Mrs Chris Williams and Dr Anne-Marie Van Dodeweerd.

Finally, we want to acknowledge the support in early stages of the late Mr Richard Price of Patchwork Technology, who sadly passed away in the early days of the project.

CONTENTS

List of Symbols

Fov_{Horiz}	camera horizontal field of view (deg)
H	height of projected field of view at distance L from camera (m)
h	height of image on camera focal plane (mm)
CCD_w	width of camera CCD
F_{Length}	camera focal length
Fov_{Vert}	camera vertical field of view
CCD_h	height of camera CCD
H_{pix}	number of pixels in CCD (height)
W_{pix}	number of pixels in CCD (width)
S_{pix}	size of pixel projected to the object
P_{length}	projected length of the image in the direction of carrier platform motion
V_{ang}	angle of camera boresight up from vertical downward (nadir) (in degrees)
D	diameter of camera optical system
f	distance inside camera from optical center of lens to focal plane
θ	camera field of regard (degrees)
Σ	covariance
x	sample feature vector
μ	feature mean
D^2	Mahalanobis distance squared

1 ABSTRACT

The project investigated whether it would be possible to remove the main technical hindrance to precision application of herbicides to arable crops in the UK, namely creating geo-referenced weed maps for each field. The ultimate goal is an information system so that agronomists and farmers can plan precision weed control and create spraying maps. The project focussed on black-grass in wheat, but research was also carried out on barley and beans and on wild-oats, barren brome, rye-grass, cleavers and thistles which form stable patches in arable fields. Farmers may also make special efforts to control them.

Using cameras mounted on farm machinery, the project explored the feasibility of automating the process of mapping black-grass in fields. Geo-referenced images were captured from June to December 2009, using sprayers, a tractor, combine harvesters and on foot. Cameras were mounted on the sprayer boom, on windows or on top of tractor and combine cabs and images were captured with a range of vibration levels and at speeds up to 20 km h^{-1}.

For acceptability to farmers, it was important that every image containing black-grass was classified as containing black-grass; false negatives are highly undesirable. The software algorithms recorded no false negatives in sample images analysed to date, although some black-grass heads were unclassified and there were also false positives.

The density of black-grass heads per unit area estimated by machine vision increased as a linear function of the actual density with a mean detection rate of 47% of black-grass heads in sample images at T3 within a density range of 13 to 1230 heads m^{-2}.

A final part of the project was to create geo-referenced weed maps using software written in previous HGCA-funded projects and two examples show that geo-location by machine vision compares well with manually-mapped weed patches.

The consortium therefore demonstrated for the first time the feasibility of using a GPS-linked computer-controlled camera system mounted on farm machinery (tractor, sprayer or combine) to geo-reference black-grass in winter wheat between black-grass head emergence and seed shedding.

2 SUMMARY

Concerns about food security may be exacerbated by increased demand for food associated with predicted increases in the UK population. The UK population is predicted to increase by 4.3 million to over 65 million by 2018 and, if the current rate of increase continues, the population would reach 71.6 million by 2033 (ONS, 2009). On the other hand, UK cereal and oilseed production could decline if herbicides lose approval for use due to the European Union (EU) Directive 91/414/EEC, the EU Water Framework Directive and restrictions due to the EU Parliament's Environment, Public Health and Food Safety Committee (Clarke *et al.,* 2008). Retailers also have to address concerns of consumers about pesticide inputs to crops. There is, therefore, a need for solutions to the problem of maintaining crop yields and production in ways which meet both legislation and market acceptability, and minimise environmental impact while successfully controlling weeds, pests and diseases. This project focuses on weed control aiming to contribute towards achieving these goals in the long-term.

Weed patches. Weeds often occur in patches in arable fields. These patches may relate to differences in topography, aspect, fertility or soil type and conditions within the field, or quite simply to the place where the weed was/is being introduced. Since patches of non-wind dispersed weeds are relatively stable, weed mapping merits further study in order to raise the accuracy of weed maps and the ease of mapping to reach acceptable standards for precision farming and SSWM (site-specific weed management).

Mapping patches. The attractions of map-based patch spraying are both economic and environmental. Lutman & Miller (2007) reported, however, that "few farmers have adopted site-specific weed management" because of "a great reluctance … to spend time creating maps. They would much prefer automated detection systems". The lack of an automated system for weed mapping is, therefore, a clear obstacle to adoption of SSWM and is the main problem addressed in this project.

The project, therefore, sought to prove the concept of automating the weed mapping process using machine vision. If the concept is proven, then, subject to further development, the main technological hindrance to the precision application of herbicides to arable crops in the UK, could be removed. The long-term goal is

therefore to help maintain crop productivity and reduce production costs, while satisfying existing EU regulations on the approval and use of herbicides and perhaps allowing retention of products likely to lose approval. The project particularly focussed on weed control in key UK arable crops wheat and barley, but results should also be relevant for oilseed rape, potatoes, sugar beet and field scale pulse crops.

Why only a one-year project to prove the concept? The main difficulty of automating weed mapping is weed identification by machine vision and so before embarking on a project to develop a complete system, it was essential to demonstrate the feasibility of (a) using farm machinery to capture images of sufficient quality and (b) developing algorithms to identify weeds using these images. An adequate system must cope with different crop backgrounds and lighting levels, and identify different weeds, but for proof of concept, the project has particularly focussed on black-grass in winter wheat.

Real-time versus offline systems. Previous research including the DEFRA/HGCA LINK patch weeding project, demonstrated the possibility of using a weed map to control the sprayer and apply herbicides on a spatially selective basis. As pointed out by Lutman *et al.* (2002), "map-based patch spraying has a number of advantages over real-time treatment. The availability of the weed map prior to treatment provides an opportunity for the user to reflect on product choice and dose prior to use, and to estimate precisely product requirements so that the risk of putting too much herbicide solution in the sprayer is minimised." Images captured in real-time must therefore be processed offline to identify weeds and create weed maps. The data collection rates and total storage capacity required for this are challenging but within the capability of state-of-the-art commercially-available computers, GPS, and digital imaging hardware. Also, performing the machine vision task offline affords the opportunity to apply a higher level of computing power than would be feasible in a field-based real-time computer vision system.

The ultimate goal of creating weed maps is to provide an information system so that agronomists and farmers can plan precision weed control and create spraying maps and the overall approach to precision weed control is illustrated in Figure I. In addition to the particular focus on black-grass in wheat, some research was carried out on barley and winter beans and on wild-oats, barren brome, rye-grass, cleavers and thistles. These weeds were chosen as they frequently occur and persist in relatively stable patches in arable fields, farmers have to make special and sometimes expensive efforts to control them, and resistance to herbicides is problematical in grass weeds.

Image capture. The project explored the feasibility of automating the process of mapping black-grass in fields by capturing geo-referenced images using cameras mounted on farm machinery. Images were collected from June to December 2009, using sprayers and tractors (June 2009), combine harvesters at harvest (August 2009) and tractors pre- and post-drilling (October 2009). Supplementary image capture was carried out at various times to December 2009 walking through parts of fields using a camera on a monopod. Images were captured with a range of vibration levels and at speeds up to 20 km h^{-1}. Analysable images were obtained at 14 km h^{-1} but not at 20 km h^{-1}.

The machine vision system employed used a computer-controlled high resolution digital SLR camera (Nikon D90, capturing at 0.5 frames per second (fps), 4288x2848 pixels per image) and some research was also carried out with a progressive scan, digital video camera (up to 30 fps, 1280 x 960 pixels per frame). Cameras were mounted on the sprayer boom, on windows or on top of tractor and combine cabs. A detailed hardware specification is provided in the report.

Image analysis. Geo-referenced, time/date stamped images were captured in the field. The most challenging part of the project was to use these images to identify grass-weeds in fully-grown crop canopies. Given the timescale of the project, the project management committee agreed to focus on proving the concept using black-grass in wheat at T3. For acceptability to farmers and HGCA levy payers in general, it is very important that every image containing black-grass is classified as containing black-grass; false negatives are hazardous. The software algorithms developed asuccessfully identified black-grass in the images analysed to date, although significant numbers of black-grass heads were unclassified. It is important to recognise that these results are from a single season and a small number of fields. This absence of false negatives in images illustrates the considerable progress made in this short project. From a practical perspective, and to satisfy wider environmental concerns both of DEFRA and the general public, false positives are also undesirable as weed control would then be demanded when unnecessary.

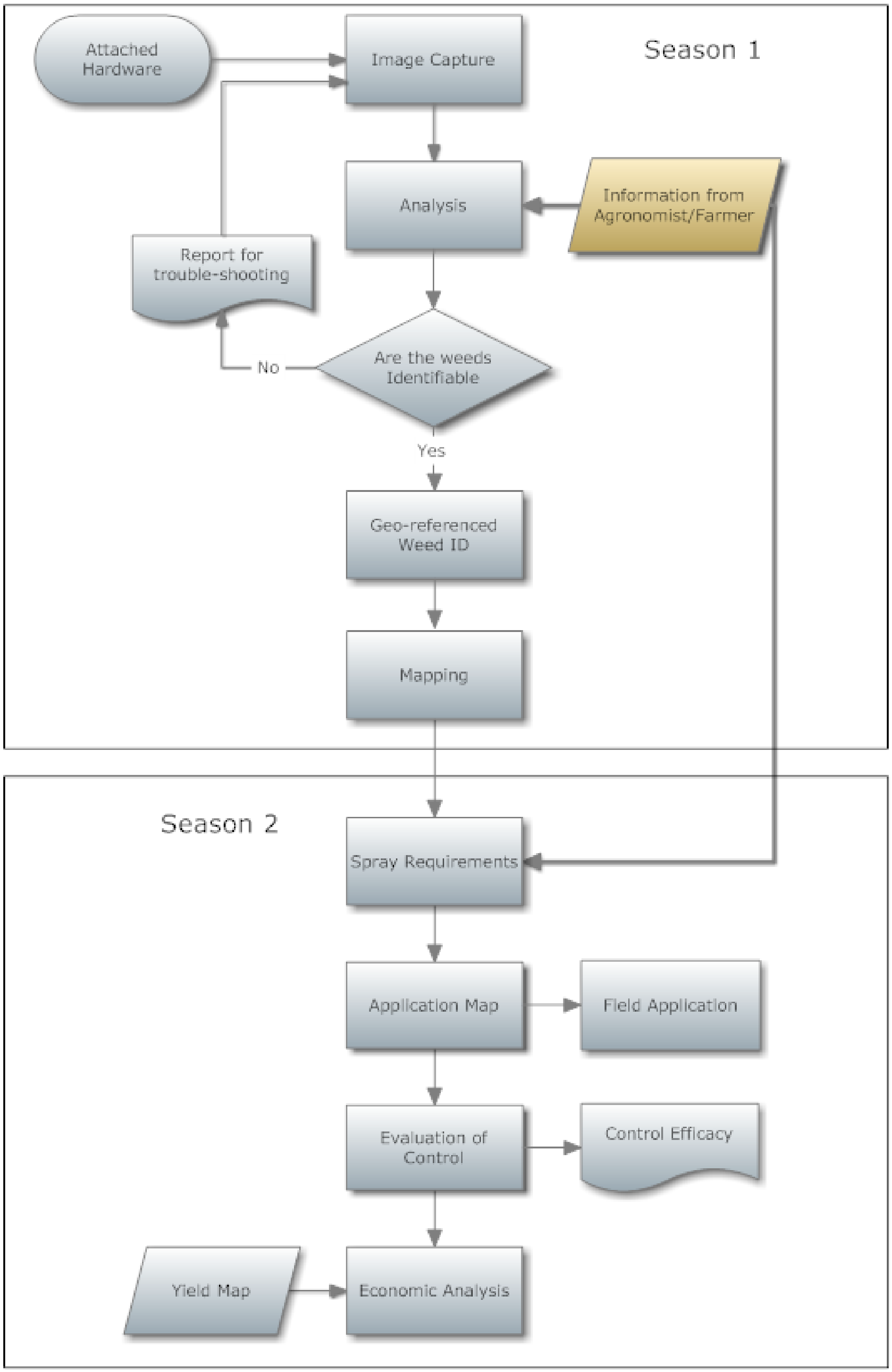


Figure I. System concept of precision weed control based on weed mapping in the first season and control in the next.

In practice, mapping may continue in the second and subsequent seasons to update the weed map and improve its accuracy. The system aims to automate the drudgery of weed mapping but expert, local knowledge from agronomists and farmers is indispensable, especially as highlighted.

We have not only analysed images for presence or absence of black-grass but also estimated the density of black-grass heads per unit area by machine vision. For acceptability to levy payers, almost every black-grass head at low density needs to be detected (to avoid false negatives) but the higher the density, the lower the detection rate needed. Although the images where every head was detected had low densities, the correlation between the percentage of heads detected and black-grass density was not significant and there was a mean detection of 47% of black-grass heads in all images at T3 within a density range of 13 to 1230 heads m^{-2}.

Improving performance. Failure to detect occurred partly because results presented were for only a partial segmentation of histogram hue and value bands and partly due to background clutter and occlusion of black-grass heads by each other or by other objects in the image. A significant number of objects in images were classified incorrectly and so these heads are false positives. Flowering (anthesis) did not affect detection, but very dark heads, which will have a low HSV value signal may not be classified.

Why are there false positives? The main reason for the false positives for black-grass detection is that a preliminary classifier was used based on the average width, length and some basic shape and colour characteristics. As this classifier is expanded to include the full set of features necessary to classify objects as black-grass, wild-oats, barren brome, crop heads and leaves, the numbers of false positives and undetected black-grass heads will decline. The purpose at this stage was to demonstrate detection of black-grass heads in each image.

One important part of the research was to make the algorithms adaptive to variable conditions. This leading edge research was achieved without using the expensive dual or multi-spectral cameras favoured by some, using instead high resolution visible-only cameras. In terms of background rejection and object segmentation, we have demonstrated performance levels that meet or exceed those of multi-band cameras. This was achieved through a combination of hue, saturation, and value filtering and by taking advantage of the greater image detail provided by a camera with a 4288x2848 pixel charge coupled device image sensor and matching optical system. All images were converted from RGB (red-green-blue) to HSV (hue-saturation-value) signals before processing. The adoption of this approach largely explains the absence of false negatives in this research.

Weed mapping. A final part of the project was to create geo-referenced weed maps. The software for this was written in previous HGCA-funded projects and the process is therefore relatively straightforward. As proof of concept, we provide two examples showing that geo-location by machine vision compares well with manually-mapped weed patches.

The consortium demonstrated for the first time the feasibility of using a GPS-linked computer-controlled camera system mounted on farm machinery (tractor, sprayer or combine) to geo-reference black-grass in winter wheat between black-grass head emergence and seed shedding. A follow-on project funded by the UK government Technology Strategy Board will seek to refine the algorithms for black-grass, adapt them for other important weeds and develop a pre-commercial system.

2.1 Key Take-Home Messages for HGCA Levy Payers

The concept of automated mapping of uncontrolled black-grass in winter wheat has been proven in principle and should be developed to aid farmers and agronomists in site specific weed management and detection of potential herbicide resistance.

Funding is, however, required to make the system of use to levy-payers. Specifically research is needed as follows:

- Algorithm development to ensure algorithms are adaptive to different conditions found in UK and in different seasons, in different crops, to different weed species and at different crop and weed growth stages;
- Software development to link maps created at different times in order to improve confidence of users in the maps and to confirm inter-seasonal correlations of infestations on a field scale;
- Application testing in the field combined with economic analysis; and
- Development of a pre-commercial system capable of scanning whole fields as an integrated, cab-mounted system unit including portable camera(s), GPS receiver and single board computer.

3 TECHNICAL DETAIL

3.1 Introduction

Concerns about food security may be exacerbated by increased demand for food associated with predicted increases in the UK population. The UK population is predicted to increase by 4.3 million to over 65 million by 2018 and, if the current rate of increase continues, the population would reach 71.6 million by 2033 (ONS, 2009). On the other hand, UK cereal and oilseed production could decline if herbicides lose approval for use due to the European Union (EU) Directive 91/414/EEC, the EU Water Framework Directive and restrictions due to the EU Parliament's Environment, Public Health and Food Safety Committee(Clarke *et al.,* 2008). Retailers also have to address concerns of consumers about pesticide inputs to crops. There is, therefore, a need for solutions to the problem of maintaining crop yields and production in ways which successfully control weeds, pests and diseases while meeting both legislation and market acceptability, and minimising adverse environmental impacts. This project focuses on weed control aiming to contribute towards achieving these goals.

Weeds often occur in patches in arable fields (Heijting, 2007; Lutman & Miller, 2007). These patches may relate to differences in topography, aspect, fertility or soil type and conditions within the field, or quite simply to the place where the weed was/is being introduced. Since weed patches of non-wind dispersed weeds are relatively stable (Heijting *et al.*, 2007; Lutman & Miller, 2007), weed mapping merits further study in order to raise the accuracy of weed maps and the ease of mapping to reach acceptable standards for precision farming and site-specific weed management (SSWM).

The attractions of map-based patch spraying are both economic and environmental. For example, SSWM could reduce the black-grass control cost in winter wheat by £31/ha if the application were limited to 55% of the field (Lutman & Miller, 2007). Gerhards & Oebel (2006) found that "herbicide use with a map-based approach was reduced in winter cereals by 20–79% for grass weed herbicides" with 85% to 98% control efficacy. Lutman & Miller (2007) reported, however, that "few farmers have adopted site-specific weed management" because of "a great reluctance … to spend time creating maps. They would much prefer automated detection systems". Gerhards

& Christensen (2003) likewise concluded that “weed monitoring systems are a critical component in the utilization of the ideas and knowledge developed in research projects on site-specific weed control”. The lack of an automated system for weed mapping is, therefore, a clear obstacle to adoption of SSWM (Miller & Lutman, 2008) and is the main problem addressed in this project.

This proposal, therefore, aims to prove the concept of automating the weed mapping process using machine vision. If the concept is proven, then, subject to further development, the main technological hindrance to the precision application of herbicides to arable crops in the UK, could be removed. "Precision in decision making leads to decreased use of inputs, less environmental emissions and enhanced profitability—all essential to sustainable systems" (Day *et al.,* 2008). The long-term goal is therefore to help maintain crop productivity and reduce production costs, while satisfying existing EU regulations on the approval and use of herbicides and perhaps allowing retention of products likely to lose approval. The project particularly focuses on weed control in key UK arable crops wheat and barley, but results will also be relevant for oilseed rape, potatoes, sugar beet and field scale pulse crops.

Why only a one-year project to prove the concept? The main difficulty of automating weed mapping is weed identification by machine vision. An adequate system must cope with different crop backgrounds and lighting levels. In addition, some important weeds are similar in appearance to the crop and need to be identified in dense crop canopies. In the vegetative growth stages, when weed control needs to be applied, some weeds are particularly challenging to identify even by trained personnel and are probably impossible to distinguish from the crop by machine vision (e.g. wild-oats, black-grass, meadow-grasses and barren brome in cereals; charlock in oilseed rape).

Several research groups are investigating weed identification by machine vision with varying success, with a view to developing both real-time systems for weed identification and immediate treatment and/or map-based systems (e.g. Dammer & Wartenberg, 2007; Gerhards & Christensen, 2003; Gerhards & Oebel, 2006; Nordmeyer, 2006, 2008; DEFRA Horticulture Link project on volunteer potatoes in vegetables in the UK). None of these systems is yet commercialised and their application to broad-acre crops, such as winter cereals, is difficult due to the variable emergence times of weeds, the problem of identifying vegetative grass weeds in cereal crops, not to mention the implicit need to redesign sprayers with multiple nozzles/booms to cope with different herbicides for different weed groups. Even if identifications were feasible, the large areas and high work rates required in arable farming systems give other problems for real-time control systems. There may be safety issues in relation to the transport and/or disposal of unused herbicides in sprayers at the end of each day. A novel approach to weed mapping is, therefore, required.

Previous research including the DEFRA/HGCA LINK patch weeding project, demonstrated the possibility of using a weed map to control the sprayer and apply herbicides on a spatially selective basis (Lutman *et al.*, 2002). The project builds on this previous research. As pointed out by Lutman *et al.* (2002), "map-based patch spraying has a number of advantages over real-time treatment. The availability of the weed map prior to treatment provides an opportunity for the user to reflect on product choice and dose prior to use, and to estimate precisely product requirements so that the risk of putting too much herbicide solution in the sprayer is minimised." Images captured in real-time must therefore be processed offline to identify weeds and create weed maps. The data collection rates and total storage capacity required for this are challenging but within the capability of state-of-the-art commercially-available computers, GPS, and digital imaging hardware. Also, performing the machine vision task offline affords the opportunity to apply a higher level of computing power than would be feasible in a field-based real-time computer vision system.

3.1.1 Weed Sensing and Identification

Weed identification from captured images is the greatest challenge of the project and is linked to the weed sensing system in use. Weed sensing methods and site-specific weed control technologies have been reviewed recently by Christensen *et al.* (2009) and a detailed review is not included here. It is, however, necessary to explain why we have rejected the use of bispectral cameras. Weis (2007), like several others, used image analysis to distinguish weeds from crop plants and to identify some weeds and crops to species level. He used a dual camera system, one with a near infra-red (NIR) sensor and the second with a visible (VIS) image capture sensor. Other researchers are endeavouring to use single or paired multispectral cameras to detect weeds (e.g.

Gerhards & Oebel, 2006; Dammer & Wartenberg, 2007; Schuster *et al.*, 2007; Hamouz *et al.*, 2008). The analysis of differences between the VIS and NIR images also requires that the two images be correlated in space and time, which is achievable but relatively expensive with respect to computer hardware/software requirements. In addition, by reducing captured images to binary, Weis's algorithms may discard information about leaf surface pattern/texture, which may be valuable for weed identification and also makes separation of overlapping weeds more difficult. For these and other reasons which will become apparent from the algorithms developed in this project, it will be argued that dynamically filtered colour images from a single high-resolution camera can provide superior performance to the use of greyscale VIS and NIR images, and – importantly for a system that is ultimately intended for commercial rather than research use – at much lower cost.

3.1.2 Patch spraying

Miller (2003) and the recent HGCA-funded review (Lutman & Miller, 2007) have shown that precision targeting of applications of herbicides to weed patches in fields is technically feasible. The challenge to date has been "the development of sensing systems as components in electronic controls [and] is likely to be a key factor influencing the direction of such future developments" (Miller, 2003). Progress in such systems for arable crops has been slow since the end of the last DEFRA LINK patch weeding project in 2002. Hague *et al.* (2006) did, however, report on a machine vision system for automatically generating weed and crop density maps in cereals but it was only applicable for widely spaced cereals (25 cm between crop rows) and at early growth stages (well before canopy closure). Moreover this system was not designed to identify weed species, simply to identify weedy parts of the fields. Gerhards & Oebel (2006) described an advanced experimental prototype system which includes elements of both real-time weed detection and patch spraying. The system failed to identify 11-27% of weeds as it progressed through the field at a fast walking pace (5-8 km h^{-1}). This machine is probably the most advanced of its kind and demonstrates that weed identification is feasible with machine vision, albeit at a very slow work rate in the field. For adoption, much faster work rates are essential and sprayer designs would need to be altered to allow more than one chemical to be applied concurrently. The authors also indicated that "camera technology and image analysis algorithms [would] need to be improved". Perhaps significantly, the authors did not consider the economics of the system.

3.1.3 Specific objectives for proof of concept

The project therefore aimed to establish the feasibility of automating the weed mapping process in arable fields in the UK. The sponsors asked the consortium to focus primarily on black-grass (*Alopecurus myosuroides* Huds) but, as weeds seldom occur in isolation, we have also included some preliminary research on wild-oat (*Avena fatua* L.), barren brome (*Anisantha sterilis* (L.) Nevski), cleavers (*Galium aparine* L.) and thistle (*Cirsium arvense* (L.) Scop.).
Specific objectives of the project were as follows:

1. To develop a machine vision system capable of capturing images automatically during agricultural field operations;
2. To prove the concept that images captured by the machine vision system in (1) could be used to identify and geo-reference specific weeds in the field at appropriate times of the year;
3. To demonstrate that (a) geo-referencing of weeds in images could be matched with the physical locations of weeds of the same species in the field and (b) that the data of geo-referenced, weed plants/patches could be used to generate weed maps.

3.1.4 Hypotheses

Weed identification is an important and challenging element of automating the weed mapping process.

The first hypothesis of this proposal is negative: the accuracy of grass weed identification by machine vision based on a single visit to a field is generally inadequate to identify weeds to species level with precision needed to create post-emergence herbicide application maps.

The working hypothesis is that accurate grass weed identification can be achieved in cereal crops after inflorescences have emerged.

A further hypothesis is that the accuracy of the density of grass weeds as estimated by machine vision will be close to 100% at densities less than one per square metre but will decrease as weed density increases.

An ultimate hypothesis, which the timescale of the project did not allow to be tested is that by integrating *a priori* expert knowledge of farmers and agronomists of species present in a field with information from geo-referenced images captured automatically at different times of the year during normal field activities (cultivation, planting, spraying, fertilising, harvesting), weed maps will be developed with sufficient accuracy so that farmers with advice of their agronomists can first create and then utilise variable rate herbicide application maps for precision weed control.

3.2 Materials & Methods

General systems requirements for a possible prototype production level system were identified from which specifications for both hardware and software were derived.

To prove the concept within the one-year schedule, it was necessary to get a trial image capture system up and running rapidly. This was because the principal challenge of the project was the demonstration of the machine vision system rather than the image capture process. We therefore used a variety of manual, semi-manual and semi-automated systems for image capture (Figure 1).

3.2.1 Hardware for Proof of Concept

3.2.1.1 Image Capture Computer

Image and position data captured in the field using a GPS receiver and cameras were transferred to a ruggedised tablet PC, model DR7 86 EX with port expansion block and external USB DVD drive. All components were either powered from internal batteries or an external 12V power supply. The Unibrain camera was linked to the tablet PC via a firewire connection while the Nikon D90 was connected with a USB link. The GPS receiver was connected via a USB link. Image capture control software was written so that images could be captured from both cameras and the GPS receiver concurrently. In order to fulfil the project's second objective, the demonstration of this semi-automatic system was considered to be of less importance than the reliable capture of field images. Therefore, where performance was compromised, we opted to allow the D90 camera to capture images on to its own internal memory card and transferred them offline to the intended digital storage system. The date and time that each image was taken as well as the geo-location was included in each image file header.

3.2.1.2 Camera

The Nikon D90 (a digital SLR camera) was used to capture high quality images as soon as possible after the start of the project. Such a high-resolution camera was a deliberate choice so that we could establish the minimum image quality needed for reliable weed identification. Conversely, the frame rate was low but satisfactory for proof of concept. To achieve faster frame rates and based on an early version of the prototype specification in the results (section 3.3.1.3) Concurrent Solutions LLC selected and supplied a Unibrain Fire-i 785c (Colour): 4605 digital video camera with a 1/3" progressive scan CCD which under computer control is designed to capture images of 1.2 Mpixels (1280 x 960) at rates of up to 30 fps.

3.2.1.3 GPS Receiver

Three receivers were used. For semi-automatic image capture, we used a Raven 115 GPS Receiver and/or the GPS receiver built into the Nikon D90 camera. For manual weed-mapping and ground truth assessments we used a Garmin hand-held unit (model eTrex H, high sensitivity GPS navigator).

Interface. The GPS receiver communicates with the on-board computer through either a serial port or USB interface. The Raven GPS receiver was set to sample at 10 geo-references per second.

Power. The GPS receiver was powered by a 12V DC power supply.

3.2.1.4 Machine Vision Processing Computer

A feature of this project is that the machine vision processing was done offline. That is, it was done in a separate computer system in the laboratory rather than on-board the carrier system. Also the amount of processing time that can be used on an image was not restricted to the interval of time between the capture of two successive images. This restriction severely limits the detection and plant identification performance of a real-time computer vision system.

For off-line processing, a quad-core Central Processing Unit (CPU) with a clock speed of 2.83 GHz with 4 GBytes of RAM running Windows XP OS was used. To provide a flexible machine vision algorithm processing system, the unit contained an Intel CUDA (Compute Unified Device Architecture, Nvidia, 2007) parallel computing architecture developed by NVIDIA with dual graphics processing cards (nVidia GeForce 260GTX) being used as general-purpose parallel processing units to augment the CPU and achieve corresponding speed-ups in computations per second.

These graphics processing cards use the revised G200b GPU chip. They each have 9 Texture/Processor Clusters (TPC) with 24 Stream Processors per cluster. This gives a total of 216 Stream Processors per GPU. Each card has a GPU core clocked at 576Mhz, a Shader frequency clocked at 1242Mz and also has 896MB of gDDR3 RAM rated at 999MHz (1998MHz effective). This system was equipped with a 1TByte hard drive with 2TBytes of external drive space.

3.2.2 Image Capture

The farms supporting these activities are indicated below with lists of the dates, times, and details of crop for images collected during this research.

3.2.2.1 Farms, Dates of Image Capture and Weeds Present

Phillimore Farms (Oxon) –

June 2009: wheat and barley growth stages (GS) 59-71.

Wheat: black-grass, barren brome, meadow brome (all with inflorescences before seed shedding)

Barley: wild-oat, cleavers (field margin only), barren brome

August 2009: wheat GS 91-93 – black-grass (after seed shedding)

Computer-controlled Nikon D90 SLR camera and Unibrain DV camera mounted on combine harvesting winter wheat.

December 2009: winter bean: black-grass, cleavers (seedlings)

Sonning Farm, Reading – Several visits. Camera mounted at roof height of tractor using a range of viewing angles and forward speeds of 9, 14 and 20 km h^{-1} (Figure 1A).

Wide range of pure cereals, plus cultivated oats as a model weed in wheat near isogenic lines with different Rht genes to provide oats against dwarf, semi-dwarf and 'tall' genotypes of wheat.

Syngenta, Cambs –

June 2009: wheat and barley GS 59-71 with camera mounted on spray boom (Figure 1B) with images captured at a range of forward speeds:

Wheat: black-grass, wild-oat, poppy, bindweed, thistle, mayweed

Barley: black-grass, wild-oat, thistle

August 2009: wheat and barley GS 91-93 (Figure 1 C, D)

Black-grass and wild-oat (after seed shedding); thistle (green, flowering)

October 2009: winter wheat (post-harvest and post-emergence):

Black-grass, wild-oat (seedlings) (images collected using D90 camera mounted on cab of tractor operating at different forward speeds. In addition, a range of images were captured manually using the monopod).

Other locations and times

Herbiseed: seedlings and plants of black-grass and wild-oats (Figure 1E), seedlings of couch and cleavers (camera on monopod)

Cereals 2009: grass weed plots in cereals (hand-held camera)

Other farms near Reading: barren brome in wheat (June 2009); wild-oat and black-grass in wheat (June 2009). (Camera on monopod).

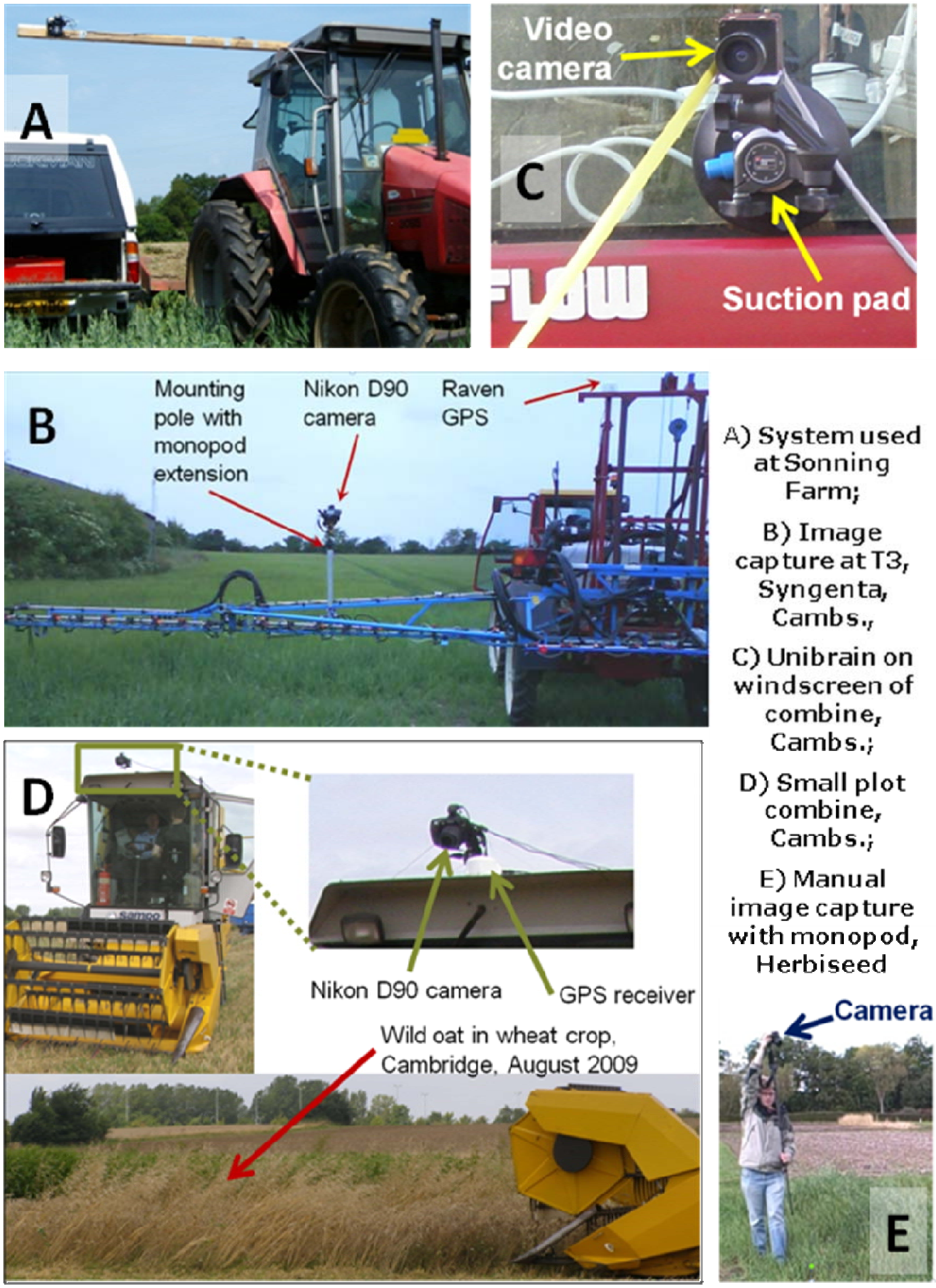


Figure 1. Camera mounting and image capture systems.

3.2.2.2 *Mounting Systems*

For manual monitoring (Figure 1E), the camera was sometimes handheld or more usually elevated on a monopod (Velbon RUP-43 or similar, maximum length 1.6 m). For mounting on cabs, the GPS unit had a magnetic base, which attached easily and securely. Cameras were mounted using high performance suction pads (Manfrotto model 241FB with Manfrotto model 056 three dimensional camera mount to allow maximum flexibility of viewing angles, see for example, Figure 1C – Manfrotto, Bassano, Italy). For mounting on the spray boom, it was essential to increase the height of the camera to obtain an appropriate viewing angle for image capture and to mimic what would be necessary to minimise spray drift on to the lens. Two such mounting systems were made, the first (Figure 1B) with 1.5 inch square section aluminium containing a monopod camera mounting insert to allow heights of 80-100 cm and a complete range of viewing angles (made by TAG, Silsoe Spray Applications Unit). A second system was made from mild steel with a 90 cm fixed length and fixed 45° viewing angle (made by University of Reading, Crops Research Unit).

3.2.2.3 *Performance Testing*

To assess performance of the image analysis system, zones within 44 images were selected for more detailed analysis. All were captured in winter wheat fields around the T3 spraying time in June 2009. By capturing at this time, the images essentially represent failure of weed control and indeed in most cases, no weed control had taken place. Thirty-five of these images contained black-grass and some also contained wild-oat panicles. They were chosen to test the hypotheses that failure to detect would increase with increase in black-grass density due to occlusion and to confirm that non-detection would be low at low density. Images were chosen to achieve a wide range of actual black-grass densities (from 0 to 1230 m^{-2}). Thirty-two images were from ‘The Railway’ field, Cambridge on 22 June (as Figure 1D) and three from Icknield Farm on chalk downland near Wallingford, Oxon (Table 1). The former were captured automatically with the camera mounted on a sprayer boom; the latter, manually using a remote control with the camera mounted on the monopod.

In addition, to test the robustness of the algorithm, nine images were selected containing no black-grass. Two of these images were captured on 22nd June in ‘House’ field near Cambridge, where winter barley was being grown (Table 1). The remaining seven images were taken on 2nd June 2009 from experimental plots containing mixtures of winter wheat and cultivated oats at Sonning Farm, Woodlands Field, near Reading (Table 1). The three fields were selected to broaden the range of environments used for performance testing.

Table 1. Image capture details for algorithm testing (June 2009).

Farm location	Camera height above ground, m	Camera viewing angle	Focal length, mm	Number of images with black-grass	Number of images without black-grass	Dimensions* of processed image, m^2
Cambridge	2.20	45°	50	32	2	1.19
Sonning	2.56	28°	32	0	7	2.16
Icknield	2.90	45°	46	3	0	4.57

*All images were taken with the same resolution of ~12 million pixels.

Where applicable, the number of black-grass heads in each image was counted both manually and also assessed by the machine vision software, developed in this project. Head counts, were converted to densities per square metre after calculating image ground area using the following formulae to calculate the field of view (F_{ov}) (horizontally and vertically) in the image:

$$Fov_{Vert} = 2 \times ((H / \cos(A)) \times (CCDw \div (2 * F_{\underline{Length}})))$$

$$Fov_{Horiz} = 2 \times ((H / \cos(A)) \times (CCDh \div (2 * F_{\underline{Length}})))$$

Where *H* is the height of the camera above the ground (m), *A* is the viewing angle of the camera, *CCDw* is the width of the CCD and *CCDh* is the height of the CCD.

A confusion matrix was constructed to show identified heads and failure of identification. A calibration curve of numbers of black-grass heads detected as a function of the actual number in the image was plotted. False positives were examined in a sample of images to assess reasons for their incorrect classification and to facilitate further software development in a follow-on project.

3.3 Results

3.3.1 Objective 1: Specification of Image Capture and Machine Vision Hardware

Projected performance requirements of specific components of the Weed Mapping system are given here. These components include the on-board computer, digital camera(s), GPS receiver and the machine vision processing computer.

3.3.1.1 General Systems Requirements

The hardware specification can be derived from a surprisingly few basic systems requirements.

User requirements: Farmers and other end-users essentially and ultimately require the system to collect images of sufficient resolution to support identification of the weeds present by machine vision and that images are to be collected over entire fields during normal field operations. It is a prerequisite that machinery speed during field operations should be unaffected by the fact that image capture is also occurring. It is also clearly essential that the system should require no interaction with the machinery operator during the actual field operation. Self-evidently some interaction would be required before and afterwards. These requirements are sufficient to derive a comprehensive set of hardware specifications for the cameras, data collection computers and the GPS receiver.

Pixel size: Based on preliminary analysis of field images and machine vision software tests, the current critical dimension d_{cr} that must be resolved in order to identify inflorescences of black-grass and wild-oat in wheat at GS 61-65 (T3) has been determined to be 2.5 mm. With at least 2 pixels (resolution cells) across this critical dimension we have set the projected pixel size S_{pix} at the target plant to be 1.25 mm. Note that for seedling identification, the critical dimension d_{cr} that must be resolved in order to identify cotyledons of broad-leaved weeds and to distinguish leaves of grass weeds has been determined to be 0.6 mm. With at least two pixels (resolution cells) across this critical dimension we have set the projected pixel size S_{pix} at the target plant to be 0.3 mm. Based on weed patch persistence, the ability to correlate geo-located images taken a different growth stages, it may be sufficient to detect the presence of grass weeds at the cotyledon stage. Calculations below relate to black-grass heads rather than seedlings.

Not all systems or users may require image capture from the entire field and indeed a lot of research has been carried out on vegetation sampling. Should this requirement be for partial sampling, the proportion of the field captured clearly depends on the platform width (e.g. a spray boom), the number of cameras, their resolution and the pixel size required for weed identification. The fraction of the field photographed decreases with increases in boom width, and with decreases in image and pixel resolutions (Table 2). To capture the majority of a field with the resolution required for black-grass recognition at T3, one high resolution camera (4288 horizontal pixels) would be required for every 5.4 m of boom width (Table 2).

Frame rate: The rate at which images must be collected is determined by the work rate of the carrier vehicle. We express this rate in units of hectares per hour and we assume that the speed of carrier vehicle will not be changed in order to collect images so the collection rate must match the work rate. That is, the images are collected at the same rate that the carrier vehicle covers the field in the performance of its primary function (e.g. cultivating, planting, spraying or harvesting).

For the purposes of calculation, assumed work rates for cultivation, planting, spraying and harvesting are 5, 0.2, 20 and 1 ha h^{-1}, respectively. The most challenging operation with respect to the data storage capacity and data transfer rate is crop spraying with a work rate of 20 ha h^{-1}. This work rate coupled with an assumption of a 12 hour working day has been used to derive the required data collection rate as well as the total storage capacity requirements.

Table 2. Maximum potential fractions of fields (%) which could be photographed by a one or two camera machine vision system.

Calculations are shown for camera(s) of three image resolutions and two pixel resolutions (0.3 or 1.25 mm), mounted on 6-36 m spray booms. For the purpose of this table, it is assumed that images are isometric (i.e. that pixel size is constant throughout the image).

	Pixels in image					Pixels in image		
horizontal	1280	1920	4288		horizontal	1280	1920	4288
vertical	960	1080	2848		vertical	960	1080	2848
	Image dimensions (metres) for pixel size of 1.25 mm					Image dimensions (metres) for pixel size of 0.3 mm		
horizontal	1.6	2.4	5.4		horizontal	0.38	0.58	1.29
vertical	1.2	1.35	3.6		vertical	0.29	0.32	0.85
	Fraction of field			6 metre boom		Fraction of field		
1 camera	27%	40%	89%		1 camera	6%	10%	21%
2 cameras	53%	80%	179%		2 cameras	13%	19%	43%
				12 metre boom				
1 camera	13%	20%	45%		1 camera	3%	5%	11%
2 cameras	27%	40%	89%		2 cameras	6%	10%	21%
				24 metre boom				
1 camera	7%	10%	22%		1 camera	2%	2%	5%
2 cameras	13%	20%	45%		2 cameras	3%	5%	11%
				36 metre boom				
1 camera	4%	7%	15%		1 camera	1%	2%	4%
2 cameras	9%	13%	30%		2 cameras	2%	3%	7%

3.3.1.2 On-board Computer

The purpose of this computer is to capture field images and geo-referencing data consisting of time-tagged GPS locations. The date and time that each image is taken must be associated with the images in some manner. Currently this is accomplished by including date and time in the image file header.

Central Processing Unit / Main Board. The critical limiting function of the on-board system is the rate at which data (images) can be transferred from the camera(s) to the mass storage device. Any CPU/Motherboard combination that does not degrade the maximum data transfer rate is acceptable. As an example specification a dual-core CPU with a clock speed of 2.0 GHz or faster is recommended as a minimal configuration.

Random Access Memory (RAM). There is no critical requirement associated with the amount of RAM for the on-board computer. However, there are standard minimal recommendations for common operating systems. One to two GBytes of RAM for Linux or Windows XP OS is recommended while 3-4 GBytes are recommended for Windows Vista or Windows 7.

Mass Storage. Given the highest required field coverage rate and assuming a 12 hour working day the total bytes of storage capacity required is given by:

$$12 \text{ h} \times 20 \text{ ha h}^{-1} \times 10^4 \text{ m}^2 \text{ ha}^{-1} \times 1.25^2 \text{ mm}^2 \text{ per pixel} \times 10^6 \text{ mm}^2 \text{ m}^{-2} \times 3 \text{ bytes per pixel}$$

$$= 11.25 \times 10^{12} \text{ bytes per 12 hour day} = 10.23 \text{ terabytes}$$

where 1 terabyte = 1,099,511,627,776 bytes. This total storage capacity requirement is a worst-case situation assuming that a sprayer will cover an average of 20 ha h^{-1} over a 12 hour day. With herbicide/pesticide replenishment, refuelling, regular breaks and time to travel between fields, a typical storage requirement could be set to a few terabytes for a commercially viable weed mapping system.

While the total storage capacity specification for this system may be overly conservative, this value is a reasonable basis to determine the maximum required data transfer rate. Based on the above analysis we can derive the maximum data rate for image capture to be:

$$11.25 \times 1012 \text{ bytes}/(12 \times 3600) \text{ seconds} = 260 \text{ Mbyte s}^{-1}$$

The maximum data rate for a standard mechanical hard-drive is around 150 MByte s^{-1}. Therefore a raid disk array could be used to attain a higher data. An alternative to the disk array is the use of a solid state hard drive (SSHD), because these have data transfer rates typically eight times higher than mechanical hard drives. In addition, SSHDs are less susceptible to vibration as they have no moving parts. SSHDs cost two to three times as much as mechanical HDs (for the same storage capacity). While the purpose of a specification is to indicate the performance requirements rather than direct the use of a particular device, a solid-state hard drive is recommended.

Human Interface. Any appropriate interface that permits system control and monitoring is sufficient. The minimal specification is a video monitor to support the review of incoming images, evaluation of the system status including available mass storage, and system operation and user/input device(s) to start and stop data collection programs. For this project we have used a 10 inch touch screen for input and output to the computer during image capture in the field and an attachable keyboard and mouse for data transfer and system configuration management.

Power. The system must be able to run on a single 12 V DC supply fed from the agricultural machinery in use and so the current must not exceed 20 Amps. The power connection interface must be compatible with accessory power sources provided on the carrier vehicles. This will include a standard AUX 12V power connector (e.g. cigarette lighter) interface. As a prototype system will be carried into the field by an unknown variety of different vehicles we cannot predict all auxiliary power connection configurations. The system must, therefore, have its own battery power source available as an alternative.

3.3.1.3 Camera

Charge-coupled Device (CCD) Resolution/Format. The required resolution of the digital camera is coupled to the size of the coverage of the camera's field-of-view (FOV) in the direction of carrier platform motion, projected onto the ground. The amount of ground area covered by the camera is a function of the focal length of the lens system attached to it. This specification is best expressed in the following formulae:

$$H_{pix} = \frac{P_{length}}{S_{pix}}$$

where P_{length} is the projected length of the image in the direction of carrier platform motion, S_{pix} is the projected size of a pixel (in the same units), and H_{pix} is the number of vertical (height) pixels required on the CCD. We can compute the FOV angle of the selected camera/lens system by:

$$P_{length} = \frac{2 \times H \times \sin(FOV_{vert} / 2)}{\tan(V_{ang})}$$

where H is the height of the camera above the ground and V_{ang} is the camera bore sight angle measured below horizontal.

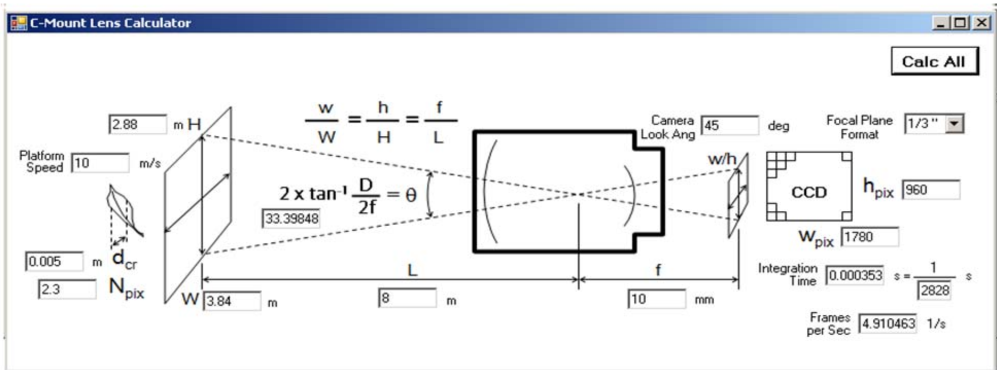
Lens System. Typically, there is a limited number of options for the number of pixels (H_{pix} x W_{pix}) in the CCD. Therefore it is sometimes useful to pick a camera and then choose a lens that achieves the required projected resolution on the critical dimension of the target plant. For example, given a camera with a CCD resolution of 3000x4000 pixels (i.e. 12 Mega-Pixels) 1/3" format (i.e. physical size of CCD), we can determine the required focal length lens system to achieve a projected pixel size of 1.25 mm.

First, a 1/3" format CCD has dimensions 3.6 mm x 4.8 mm which is a 6 mm diagonal. This diagonal dimension is used to determine the angle of view of the camera/lens system, θ.

$$\theta = 2 \times \tan^{-1} \frac{D}{2f}$$

where D is the effective diameter of the lens aperture and f is the focal length of the lens. Given the distance from the camera to the object being resolved, we can use simple geometry to convert this angle into a distance. For an object distance of approximately five metres, this camera would need a 10.5 mm focal length lens to achieve the aforementioned project pixel size of 1.25 mm at a distance of 5 m. Software was developed to facilitate these calculations more easily (**Figure 2**).

Figure 2 Screenshot of Lens Calculator for required focal length to achieve the pixel size at a known distance from camera lens



Controls. Digital cameras are equipped with a wide variety of controls for automatically setting the aperture size (effective diameter), the integration time (equivalent to shutter speed) and for automatically adjusting the focus. The camera(s) used in this application need to adjust for varying light levels while maintaining a short integration time, to prevent image motion blur. For this reason the camera must be capable of fixing the integration time while permitting auto-focus and auto-iris.

Image Capture and Data Transfer Rates. The data transfer rate derived above of 260 Mbytes s^{-1} is based on the fastest carrier platform (sprayer) running at the maximum work rate (field coverage rate) of 20 ha h^{-1}. This is a systems requirement meaning that it could be achieved with one or more cameras transferring image data to one or more on-board computers. Taking one system as an example, it is assumed that images are being collected by a single camera with CCD resolution of 3000 x 4000 pixels (i.e. a 12 Mega-Pixel camera). Such a camera would need to collect images at a minimum rate of 7.2 frames s^{-1}.

$$\frac{260 Mbyte\ s^{-1}}{3 bytes\ \ pixel^{-1} \times 12 \times 10^{6}\ pixels\ \ frame^{-1}} = 7.2\ frames\ \ s^{-1}$$

Of course, if more cameras and data collection computers were used the frame rates for each camera could be reduced accordingly.

3.3.1.4 GPS Receiver

Interface. The GPS receiver can communicate with the on-board computer through either a serial port or USB interface.

Data Sample Rate. The current data rate for the GPS receiver is set at 10 per second, with a minimum rate of one per second.

Precision. The single sample location precision is set at 5 m with a differential GPS (multiple sample) precision of approximately 1 m.

Power. The GPS receiver must provide its own power or be compatible with the 12 V DC power source provided by the carrier platform through a standard connector.

3.3.1.5 Machine Vision Processing Computer

A feature of this project is that the machine vision processing is done offline. That is, it is done in a separate computer system in the laboratory rather than on-board the carrier system. Since the computations are not real-time the hardware and performance specifications depend on the speed at which this off-line processing must be achieved. At this time, in the absence of a prescribed processing speed, 1/10 real-time is selected as a somewhat arbitrary baseline. This means that we have allotted 10 hours of machine vision processing for each hour of image collection. Of course, since machine vision processing of separate images is independent and completely parallelizable, any desired data processing rate can be achieved by multiplication of computing hardware.

In order to be able to modify and extend the machine vision algorithm processing system, we are specifying a multi-processor system such as the Intel CUDA (an acronym for **Compute Unified Device Architecture**, a parallel computing architecture developed by NVIDIA (2007)). This approach uses graphics processing units (graphics accelerator cards) as additional processing units to augment the central processing unit (CPU) of the computer and achieves corresponding speed-ups in computations per second. For image and graphics processing applications such as this, the CUDA achieves an order of magnitude better performance for the same hardware cost as compared with standard architecture multi-core (or many-core) CPUs.

Central Processing Unit / Main Board. The most cost effective choice of currently available state-of-the-art (SOA) commercial desktop computer hardware is a quad-core processor on a main board (motherboard) capable of running two or three additional graphics processing units.

Graphics Processing Units. Following the Intel CUDA guidelines (NVIDIA, 2007) these graphics processing units (GPUs) should run at 2.0 GHz or greater and provide ~1 GByte of random access memory (RAM).

Random Access Memory (RAM). This system should be equipped with a minimum of 8 GBytes of compatible high speed random access memory.

Mass Storage. The amount of storage depends on the number of hectares of field data that will be archived. It is recommended that the system be equipped with at least a 2 terabyte hard drive and an additional capability to store and access 12 more terabytes through external drives. The system should be able to access additional storage as needed through a local area network and or internet connection depending on the eventual configuration of the prototype system.

3.3.2 Objective 2a. Specification of Software for Machine Vision and Geo-referencing for Weed Mapping in Cereal Crops

The purpose of the machine vision software is to differentiate between the cereal crop and a number of weeds including black-grass, barren brome, wild-oats and cleavers at some stage during the crop planting/growth/harvest cycle. While no specific performance level requirements have been placed on this research by the sponsors, it being a proof of concept, the researchers have agreed to endeavour to achieve best possible performance and to report the levels achieved within the time-span of the project. Improvements are expected as a wider range of images becomes available. It is also true that performance will vary with growth stage and environment. In the following, we will provide details of specific algorithmic methods and give a specification for the overall approach being implemented.

3.3.2.1 Signal-Level Processing

Signal-level processing refers to the image processing functions applied to bitmap images. At this level, every pixel of the image is treated in the same manner. The purpose of signal-level processing is to prepare the image for extraction of a set of features applicable to solving the specific machine vision problem(s) of the application. All signal-level processing must support the extraction of image features at a pixel resolution of 1.25 mm as indicated in the General Systems Requirements above.

3.3.2.2 Syntactic-Level Processing

The purpose of syntactic-level processing is to extract a list of pertinent features about potential objects of interest in the images. These include object area, perimeter, shape, internal colour and texture patterns, as well as object locations within the image. One of the side benefits of syntactic-level processing is a significant data reduction, from millions of pixels to several bytes of data for each candidate object of interest.

3.3.2.3 Semantic-Level Processing

In semantic-level processing the number and relative locations of the candidate objects collected in syntactic-level processing are used to extract meaning about the image containing the candidate objects. The relationships between candidate object features support object type classification decisions, i.e. weed identification.

3.3.2.4 Geo-Referencing Software

Geo-Positioning. In this project we relied on the built-in software provided with the GPS receiver to determine the location of the camera carrier platform at the time each image was taken. The precision of this position measurement is of the order of one metre using the built-in differential GPS software. This level of precision assumes that a sufficient number of GPS satellites are detected to support the position measurement. In the unlikely event that there is not a clear line-of-sight to the GPS satellites the data collection process should notify the software user and/or tag the images with a message indicating that precision measurements will be at a lower precision.

Direction Determination. The direction of motion of the carrier platform will be specified using a combination of position measurements. The resulting precision of the direction of motion will be assumed to meet or exceed the precision achievable through an application of simple geometry to the position measurements and their uncertainties.

For example, given two position measurements with a precision of ±1 metre and separated by a distance of 20 m, the worst-case error in direction would be

arctan (2/20) = 11.3 degrees.

The expected error in direction based on a best fit to North position measurements, assuming straight line motion, would be given by the worst-case error reduced by the root summed square (RSS) of the North measurements.

For example, given ten measurements over a distance of 20 m each with a precision of one metre, the expected error in direction is

arctan (2/20) /(10)1/2 = 11.3/3.16 = 3.6 degrees.

Absolute Plant Location. The position of each object of interest in an image is determined using a projection of the image given the known position and orientation of the camera with respect to the location and heading (direction of motion) of the carrier platform at the time the image was taken. In addition the field-of-view of the camera must be known to determine the extent of the image as projected onto the ground. Details of this calculation are provided in the section 3.3.1.3.

3.3.3 Objective 2b: Implementation of Software Specification for Grass Weed Identification in Cereal Crops

This section gives details of and results from the three levels of software constructs for computer processing of field images in order to identify grass weeds in commercial cereal crops (see sections 3.3.2.1, 3.3.2.2, 3.3.2.3). Most of this research has concentrated on black-grass with a smaller amount of work on wild-oat (which has not been reported here). Image processing functions were mostly implemented using OpenCV (Bradske & Kaebler, 2007) an open source image processing library available for a wide variety of computer operating systems and hardware platforms including Microsoft OS and Intel PC processing systems.

3.3.3.1 Segmentation

Segmentation of an image is one of the first steps of image analysis used when trying to identify the content of an image. It is generally regarded as the process of separating background information from foreground information. Of course what is background and what is foreground depends on the problem being solved. Segmentation can be an easy first step in extracting information, as the following example will show.

At early growth stages, living green plants in the foreground are easily separated from the background soil using an excessive green filter to isolate the greener parts of an image (Figure 3). The segmentation problem becomes more difficult at later crop growth stages after canopy closure, when the task is to separate two or more overlapping, living, green plants from each other in a single image

Figure 3. Images of living plants before (left) and after (right) segmentation using a simple excessive green thresholding filter. Upper pair are mostly broad-leaved. Lower pair are black-grass (circled) and wheat at Cambridge on 15 October 2009.

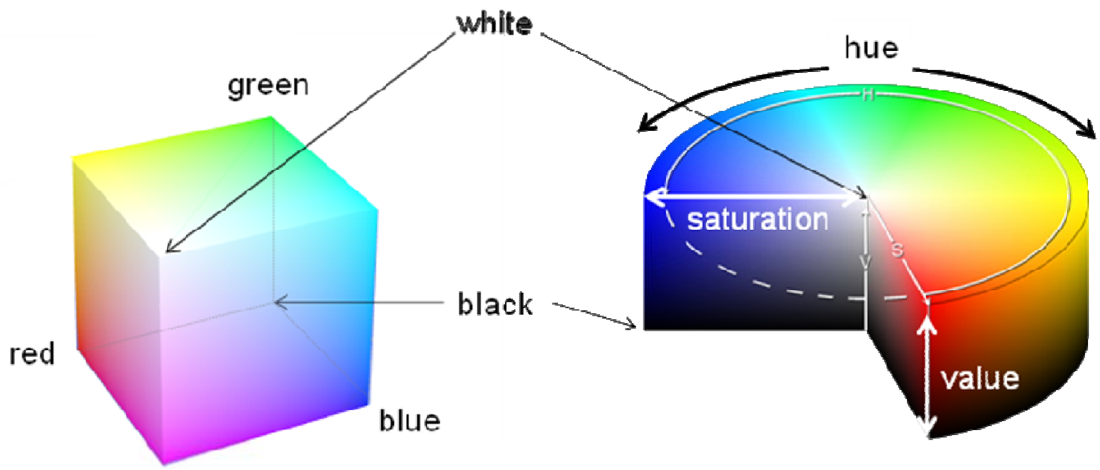
3.3.3.2 Segmentation based on Hue and Value Thresholding adaptively variable according to Image Content

A problem that was encountered early in the project was a failure to segment satisfactorily using normal thresholding techniques. The vegetation in the images to be processed, which is the result of nine months' plant growth and development and is often characterised by dense canopies, are by their very nature extremely complex. Standard thresholding techniques fail to segment the majority of the image into objects that can be usefully stored.

Rather than segmenting on dominant green, which separates green plants from everything else, it is more effective to segment closed canopies on multiple overlapping hue and value passbands in different colours and brightness levels, as this helps to separate plants by species and growth stage. The exact passband into which a plant falls is not critical, but rather a reduction in image complexity. The image is then segmented further by separating objects grouped by their dominant orientation. Each technique will be described in turn.

A brief review of the field images collected for this research makes it clear that an alternative approach is needed. Rather than hard-coding the band values into the source code, the hue passbands are set based on the image content itself. Converting from RGB to HSV (Figure 4) reduces the number of colour parameters from three to one and makes it easier to generate multiple segmentations based on narrow bands of colour. Also, the overall brightness of objects (value) can be used to segment the image by object group.

Figure 4. Comparison of the three colour signals in an RGB (Red, Green, Blue; the cube on the left) system with HSV (Hue, Saturation, Value; the cylinder) signals. Colour in HSV is a single signal, the value signal is a measure of darkness/brightness and saturation is the colour saturation.



The program constructs histograms from the hue and value channels to find the predominant colour and value bands which are likely to represent large groups of similar objects. The peaks and valleys of the histogram can be used to set the hue and value band limits for each segmentation.

Each segmented band is converted into greyscale and passed to an edge detection filter. This filter creates contours along object edges. A high spatial resolution of the images is essential for this edge detection process and is a major reason why this visible-only approach is needed to achieve high performance levels in weed identification. These contours are stored as the outlines of candidate objects. The end result of the algorithm is, therefore, objects that come from different hue/value bands in the image. This process provides a way to extract more objects from an image than normal segmentation. The key element is that the bands' values used for segmentation are a function of the image characteristics avoiding reliance on any hardcoded values. Since all these candidate objects are eventually recombined into a single list before they are passed to the classifier, the particular segmentation path taken by each object is not an issue.

3.3.3.3 Segmentation by Orientation Filtering with a "Rotating Bow tie"

As is evident in Figure 5 objects of interest in an image can sometimes occlude each other. In these cases colour and value band segmentation fails to separate them. In order to combat this and to extract whole candidate objects, a method of separation by orientation has been included, called the rotating bow tie method.

Figure 5. An original image before any processing has taken placed.

An image 'pipeline' is first used to extract the information of interest. A series of filters is thus applied to the original image in succession, each new filter processing the output of the previous filter. The image is transformed to greyscale (Figure 6), in order to remove the colour information (which is not needed for 'rotating bow tie').

Figure 6. Scene showing the image after converting to grey scale.

Figure 7. Scene showing the image when a horizontal orientation filter has been applied to Figure 6.

The image is then run through an orientation filter (similar to a Sobel operator template) that brings out groups of pixels with that particular orientation (Figure 7).

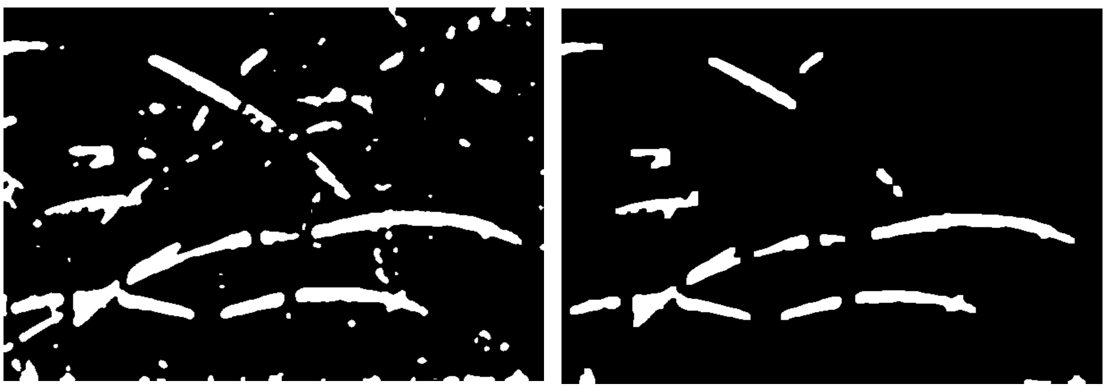
The reason the algorithm is called a rotating bowtie is that each pass of the filter has a template of values in a pattern that resembles a bow tie. The current bow tie algorithm uses eight different filters each filtering a range of 22.5° thus accounting for the full range of 180° for object orientations.

The greyscale image is then blurred by using a smoothing (Gaussian) filter to remove areas with high spatial frequency noise from one pixel to the next that may reduce the accuracy of the orientation extraction operation (Figure 8).

A greyscale threshold is then applied passing those regions of the image whose brightness exceeds the threshold (Figure 9 left side). The image is still cluttered with many small regions where the threshold has been exceeded. Since we have a known viewing geometry and a known target set we can determine the smallest possible valid candidate object. All smaller objects are eliminated (Figure 9-right side).

Figure 8. Scene showing the image in Figure 7 after 'smoothing'.

Figure 9. The image after thresholding (left) and discarding small objects (right).



The regions that pass these filters can be used to extract other features from the original images such as colour, texture, average width and so on. The resultant binary image contains objects which can be retrieved for later computations in the classifier (the semantic processing stage when objects are identified by plant type).

The result of these two segmentation techniques means that the initial segmentation algorithm is robust against illumination changes and also changes in colour of the objects of interest. The overall process is now summarized and the next step of classification will be described.

Several new machine vision algorithms for weed detection and identification have been developed specifically for this project. Each image is passed through multiple signal processing pipelines (data flow paths indicated by a vertical column in Figure 10). The functions applied in the pipelines are pixel-level operations, which means that the functions are being applied to every pixel in the image. The names of these functions are included in (Figure 11) which shows a more detailed view of the three levels of processing for one of the pipelines.

The signal level processing includes image conditioning functions such as the HSV histogram generation, thresholding, median filtering, canny (edge detection) and dilate and erode function which help to remove small variations in the candidate object shapes. Most of the bit-level functions are well-known by the machine vision and image processing communities and are available in the open literature. At the next level, the pixels (bits) of the image are replaced with a list of candidate objects which means that the amount of data required drops from millions of bytes to a few thousand bytes depending on the number of candidate objects detected. The first step is object segmentation which has been described in detail above. A list of edge points for the contour and a median line (called the object skeleton) are generated and used to support feature extraction. Features are extracted and added to each candidate object description by analyzing the portion of the original image corresponding to the boundary contour and skeleton. All these data are then passed to the next level of processing for object classification (identification of the object type). Currently we are working with two levels of classifier. The first is a non-parametric one to separate invalid objects (artefacts). The second is a classical principal components analysis (PCA) classifier in which the most important (i.e. distinguishing) features are used to associate sample objects with the nearest object model. Details of these two classifiers appear below.

Figure 10. Illustration of multiple signal processing pipelines applied to an image to isolate objects for segmentation and classification.

The steps indicated are implemented at each stage to extract candidate objects from the image which include the plant types of interest. These objects from all pipelines are then combined before classification.

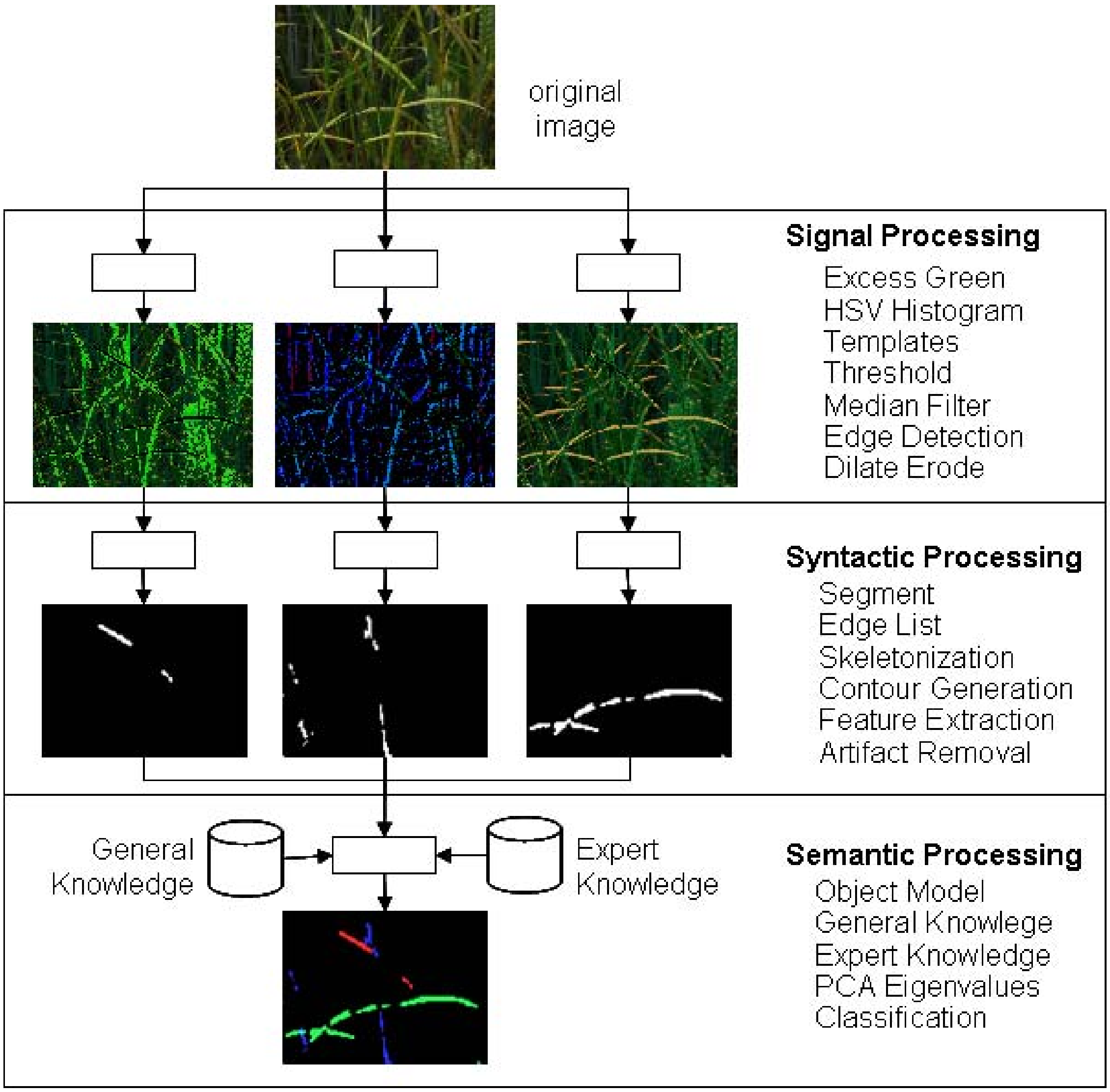
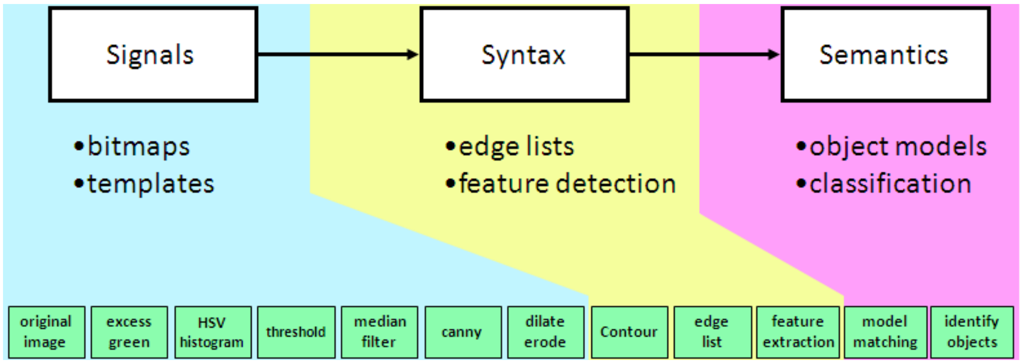


Figure 11. Details of functions for a single Image Processing Pipeline.



A simple non-parametric method based on set intersection has been implemented to eliminate artefacts. Figure 12 illustrates the process by showing the distribution of values over four of the features for black-grass and for the artefacts surrounding black-grass. For each feature we see that the means of the black-grass and the associated artefacts are similar. However due to the random nature of the artefact values it is very unlikely that all the features for a particular sample will be close to the mean values for black-grass. We can, therefore, set boundary values for each feature that will lead to an object passing the black-grass 'test', but which will lead to rejection of the artefacts for one or more of the features. In other words an artefact will be accepted as a candidate valid object for further processing only if it is in the membership set of all features.

Many of the candidate objects are not valid objects but are artefacts of skeletonisation (a function of syntactic processing). The vast majority of these have features unlike any object of interest (e.g. they might be leaves and therefore not of interest in a wheat crop with black-grass at T3) and they can, therefore, be easily removed. Artefact removal is important to reduce the computational load on the subsequent pattern classification process.

Figure 12. Feature values for black-grass and artefacts in a training set of objects.

The x-axis is the object index. Symbols are black-grass (blue) and artefacts (pink). The figure is an example of the use set intersection to reject artefacts from further consideration in the classification process. Shaded areas are y-axis values containing valid candidate objects.

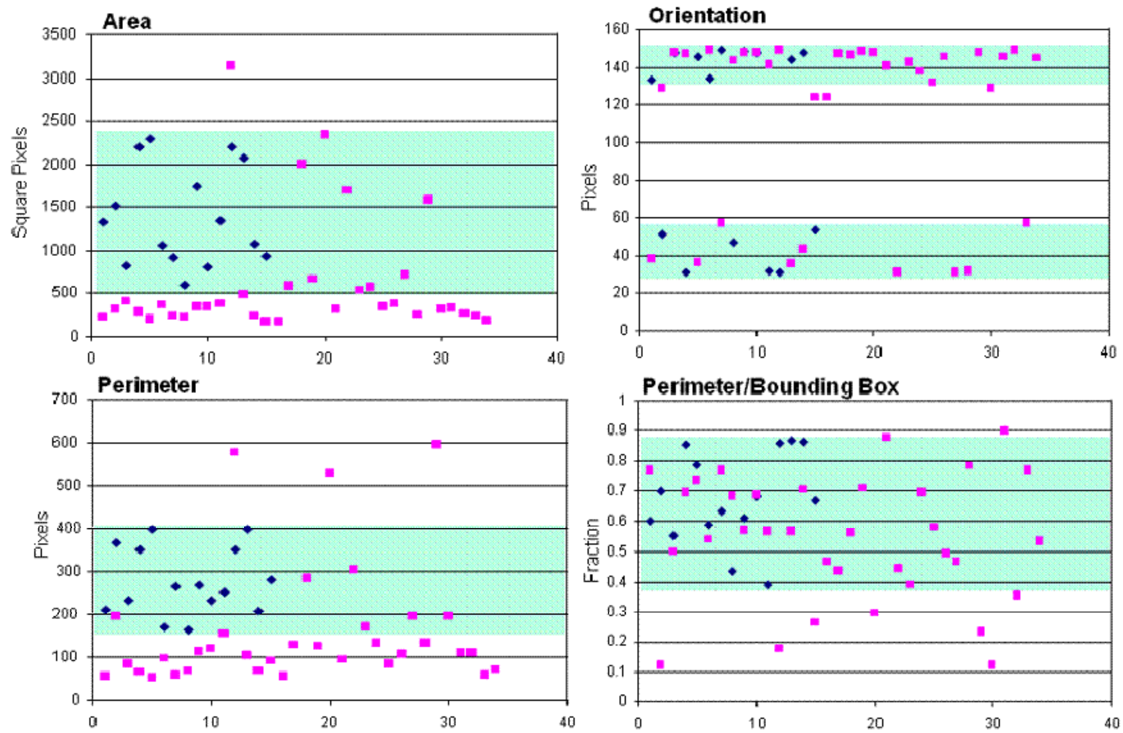
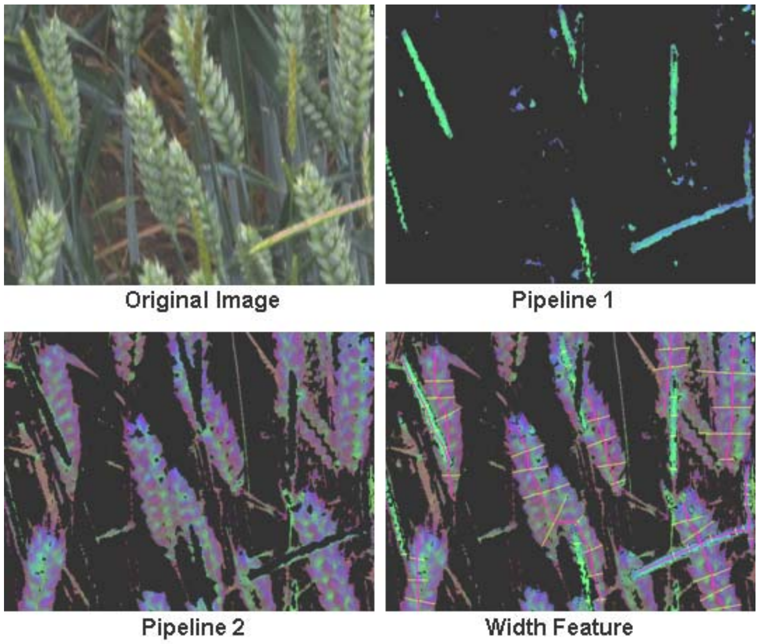


Figure 13 shows the output of two different signal processing pipelines. Each pipeline is processed separately to extract candidate objects for feature extraction. The determination of the object width feature along the skeleton is shown.

Figure 13. Two pipeline outputs with width feature detection shown in bottom right.



The candidate object lists are passed to the next level of processing for object identification. At this stage the relative positions, orientations, similarity in colours and textures between neighbouring objects are used to support the determination of plant types. In this semantic processing level we are extracting meaning from the relationships between the syntactic elements.

Both general and expert knowledge are needed to support the object identification process. Expert knowledge includes details about the physical characteristics of plants and the effects of a variety of environmental conditions on plant growth. The machine vision system has no innate understanding of the physical world. To achieve the best performance it is necessary to codify essential general knowledge into the process as well. A general knowledge rule base formulated for weed identification is therefore required, an excerpt from which is shown (Table 3).

Table 3. Rules used in developing valid object detection in images after segmentation. The lists of numbers on the right indicate whether a rule is derived from other rules or is based on first-principles (1).

Rule	Statement	Rule List		
1	**First principles**			
2	Light is from above.	1		
3	Plants grow toward light.	1		
4	Gravity bends plants and plant parts downward.	1		
5	Each plant type of interest, physical characteristics are well known and distinguishable.	1		
6	Plant sizes of each type are relatively uniform.	1		
7	Camera geometry is fixed and known.	1		
8	Land base is relatively flat and horizontal.	1		
9	Crop density relatively uniform.	1		
10	Taller plants will have a generally higher value (brightness).	2		
11	Light levels drop as perpendicular to surface points away from direction of light.	1		
12	For a given material colour, there is a deterministic relationship between the hue saturation and value as a function of light level.	1		
13	For black-grass heads, the object centroid will be on or below the skeleton.	4	5	
14	Two objects cannot occupy the same space at the same time.	1		
15	Co-located skeletons from separate processing pipelines represent the same object and should be combined.	14		
16	A method for stitching together skeletons of black-grass heads is possible based on predictable changes in HSV with light level.	5	11	12
17	Object contours can be simplified based on known plant shapes.	5		
18	Candidate objects with skeletons that fall within the contour of identified objects can be eliminated as redundant and/or artefacts.	14	17	

Such rules are used as the basis for the development of valid object detection and recognition functions by the algorithm developer. Although many of the rules of general knowledge seem obvious to the human observer, the machine vision system cannot make use of them without explicit implementation. For example the first-principles rule "Light is from above" is used to predict that the top portions of plant leaves and seed heads will tend to have higher colour values (are brighter) than the bottom portions. A human observer automatically interprets this as an indication of the shape (e.g. convex rather than concave) but the machine vision system can make no such contextual assumptions.

The exploitation of expert and general knowledge leads to the development of probabilistic models for each plant type. The presence or absence of any particular feature may not be essential to determine the species of a particular plant, but, based on a propensity of features a plant can be correctly classified with high probability.

Different plants may have similar physical characteristics, however the collected features of each plant make it distinguishable from others (at least for the plant species of interest in this study). If we think of each of the features extracted by the machine vision system as a dimension in a multi-dimensional feature space, then each plant can be placed at particular location in this feature space. The features of plants of the same species will tend to be located near each other in feature space. A feature space model can then be built for each plant type comprising the mean, μ, and covariance, Σ, of the feature sets of each sample, *x*.

$$\sum = \left\langle (x-\mu)(x-\mu)^t \right\rangle$$

Having established a model for each plant type, it is then possible to determine the model with which a particular plant sample should be associated (if any). Some features of plants are more consistent than others, so the significance of the difference between the model and a particular sample depends on this level of uncertainty. We use the Mahalanobis distance (Duda *et al.*, 2001), *D*, to place the appropriate significance on each dimension of feature space.

$$D^2 = (x-\mu)^t \sum{}^{-1} (x-\mu)$$

where Σ^{-1} is the inverse of the covariance matrix of the model. The Mahalanobis distance from two different models can be computed to determine the relative distances. If a sample must be assigned to a model then we choose the smallest value of *D*. Alternatively, association with a particular model can be based on a maximum *D* beyond which a particular sample remains unassigned.

For proof of concept, seven features were used for object identification as black-grass at T3 (Table 4). A few characteristics of the sample covariance table are worth noting. When two features are independent their corresponding covariance element will be close to zero. A number of the features are, however, highly correlated (Table 4). Hence, knowing one feature, the likely value of the correlated feature can be predicted, and so little new information is obtained by including both in the feature set. Also, the relative sizes of the variances (on the main diagonal of Table 4) vary greatly which means feature values must be normalised to ensure that the larger ones do not dominate and bias the classifier.

Table 4. Covariance matrix of features used for identification of black-grass.

A	average hue	skeleton length	average width	contour area	length of perimeter	orientation	perimeter to bounding box area ratio
average hue	**70.32**	-214.41	-13.88	-3543.72	-444.34	-73.23	-0.01
skeleton length	-214.41	**4358.52**	170.84	67274.90	9140.05	82.49	-2.35
average width	-13.88	170.84	**17.95**	4397.28	380.06	16.30	0.10
contour area	-3543.72	67274.90	4397.28	**1500000**	146057.00	2622.13	-7.65
length of perimeter	-444.34	9140.05	380.06	146057.00	**19311.50**	127.83	-5.41
orientation	-73.24	82.49	16.30	2622.13	127.83	**1864.27**	-0.84
perimeter to bounding box area ratio	-0.01	-2.34	0.09	-7.65	-5.40	-0.83	**0.02**

The issue of bias can be solved by using principal components analysis (PCA) to compute the eigenvalues and eigenvectors to normalize the object models. The eigenvalues for a highly diverse training set of images used to develop algorithms, are on the diagonal of the QR factorisation of the covariance (Table 5). Each eigenvalue is a linear combination of the features listed in Table 4. The values off the diagonal are residuals mainly due to rounding errors of the QR factorisation. Based on their relative magnitudes (the first three values along the diagonal in bold type comprise most of the variation), it may be inferred that classification of objects in images as black-grass will require no more than three principal components.

Table 5. QR factorisation from principal components analysis of training set of images of isolated black-grass heads at wheat crop GS 59-71. Eigenvalues, in descending order of magnitude, are in bold type on the diagonal from top left to bottom right of the table.

1518000	-7.81E-12	-2.93E-12	-5.03E-11	-4.34E-11	-1.18E-11	-9.08E-13
5.66E-27	**6354.19**	0	-9.15E-12	8.78E-13	5.30E-13	-1.45E-14
1.56E-33	8.95E-04	**1859.14**	-8.08E-13	1.24E-12	2.68E-13	1.72E-14
1.95E-55	-7.50E-24	3.73E-17	**57.816**	-1.53E-05	-1.55E-12	-1.85E-13
3.03E-63	3.12E-30	-1.50E-23	-1.53E-05	**18.608**	2.44E-08	9.82E-15
-7.99E-72	-5.49E-39	2.71E-32	5.03E-14	2.44E-08	**3.973**	1.49E-14
-1.86E-114	-2.54E-80	8.75E-74	8.81E-53	5.07E-47	-1.01E-37	**0.010581**

3.3.4 Performance of System

3.3.4.1 Ability to Capture Images from Moving Farm Machinery.

Images captured at 9 and 14 km h^{-1} were sufficiently well-focussed for image analysis, while those captured at 20 km h^{-1} would be too blurred for analysis (Figure 14). These images were, however, captured on a non-robust camera platform, and the use of a better damped system should give better images at higher speeds.

Figure 14. Images captured at tractor speeds of 9, 14 and 20 km h^{-1} (kph) using the Nikon D90 camera mounted on an extension piece attached to the roof of tractor cab (Figure 1A).

3.3.4.2 Results of using Pipelines

The hypothesis that fewer black-grass heads would be detected at high than at low densities was tested using the images as described in section 3.2.2.3. Quantitatively this is clearly true (Figure 15A), but, surprisingly, the proportional detection appeared to be independent of black-grass density (Figure 16), the slope of the regression line not differing significantly from zero. It should be noted, however, that every black-grass head was detected in two images at a low density, shown as images with 100% detection in Figure 16. It should also be noted that at low densities greater variability in detection rate is expected due to the small numbers of heads present in a single image – sometimes only one or two – and so failure of detection has a very large effect in percentage terms. The absence of any *false negatives* is important from the point of view of the end-user. There are, however, significant numbers of false positives, and false positives were also recorded in three out of nine images containing no black-grass as indicated in the confusion matrix (Table 6).

Figure 15. Correlation of black-grass head density in images as estimated by machine vision with actual density based on visual inspection of the image. Comparison in (A) is based on 35 images containing black-grass. There are no false negatives. False positives have been excluded in (A) and are included in (B). Key: 1:1 relationship (———); objects classified as black-grass heads in 35 images containing black-grass (◆); objects classified as black-grass heads in nine images *not* containing black-grass (▲ in (B) only). Regression lines in both (A) and (B) were fitted omitting the latter.

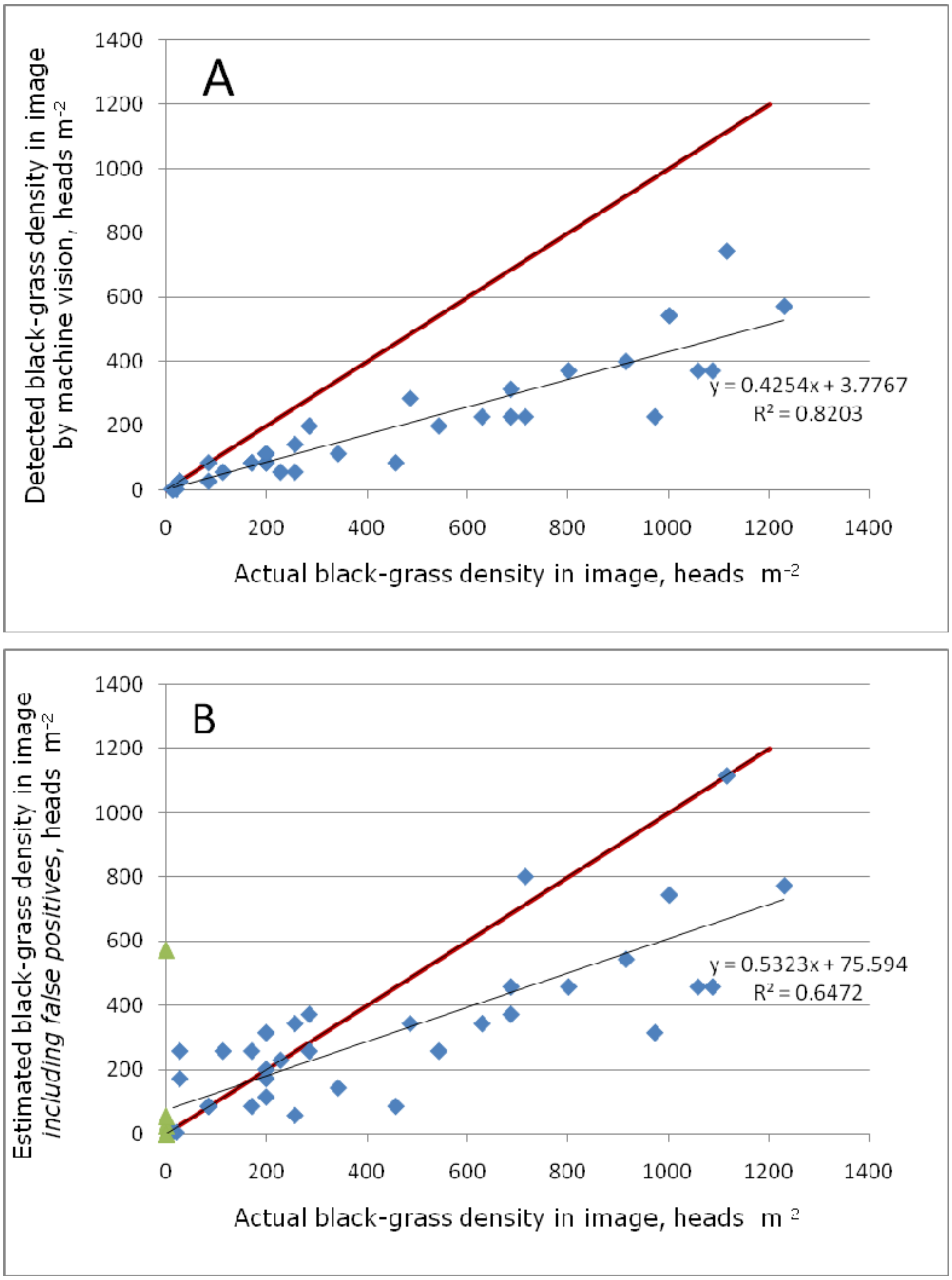
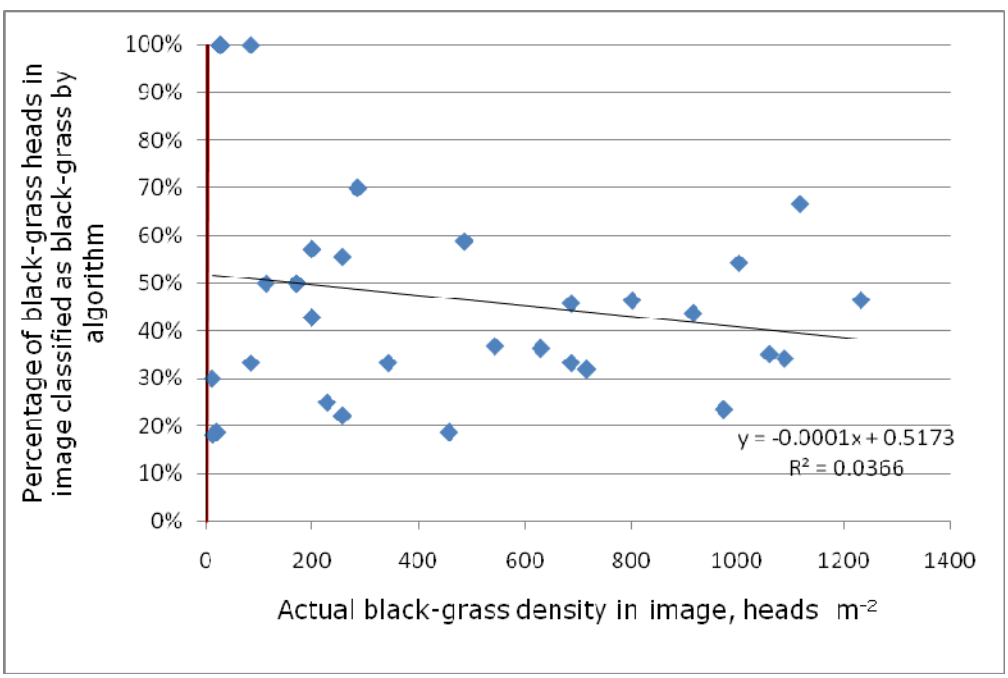


Table 6. (A) Confusion matrix for images indicating absence of false negatives but presence of some false positives. The classification of black-grass heads in these images is shown in (B).

A) Image counts	**Black-grass in image**	**No black-grass in image**
Black-grass detected in image	35	3 (false positives)
Black-grass **not** detected in image	0 (false negatives)	6

B) Head counts	**Actual black-grass heads**	**Not black-grass**
Objects classified as black-grass	244	171
Black-grass heads **not** detected	336	N/A

Figure 16. Percentage detection of black-grass heads by machine vision in 35 images in winter wheat crops at T3 at different actual black-grass head densities.



3.3.4.3 Demonstration of Detection at Low Density

Images captured in Cambridge on 22 June 2009 (Figure 17 A-H) demonstrate that images containing only one (Figure 17B,H) or very few (Figure 17D,F) black-grass heads are correctly classified as containing black-grass even though in Figure 17D two heads were not classified. It is noteworthy that all the heads in Figure 17B,F,H were correctly classified.

At very high densities of 1230 and 715 heads m^2 represented by 43 and 25 black-grass heads in Figure 18A and C, respectively, again there is no difficulty in detecting some of the heads. Failure to detect occurs partly due to background clutter and occlusion of black-grass heads by each other or by other objects in the image. For example, the clump of unclassified heads in the middle of Figure 18A is probably due to occlusion whereas at the edges of the images, a failure to classify may be due to clutter. There is, however, a significant number of objects in these images which are classified incorrectly and so these heads are false positives. Flowering (anthesis) did not affect detection (Figure 18), but very dark heads, which will have a low HSV value signal may not be classified as exemplified in Figure 19.

Why are there false positives? The main reason for the false positives for black-grass detection is that a preliminary classifier is currently in use based on the average width, length and some basic shape and colour characteristics. However, this classifier does not have the full set of features necessary to reject candidate objects that are incompatible with expert or general knowledge rules about the physical characteristics of black-grass. For example, the introduction of a feature that took into account the variability of an object would probably reduce the number of false positives.

Figure 17. Detection of black-grass by machine vision at low densities. Original images (A,C,E,G) and the same (B,D,F,H) with black grass heads either correctly classified (blue) or incorrectly *not* classified (red). NB there are no false positives.

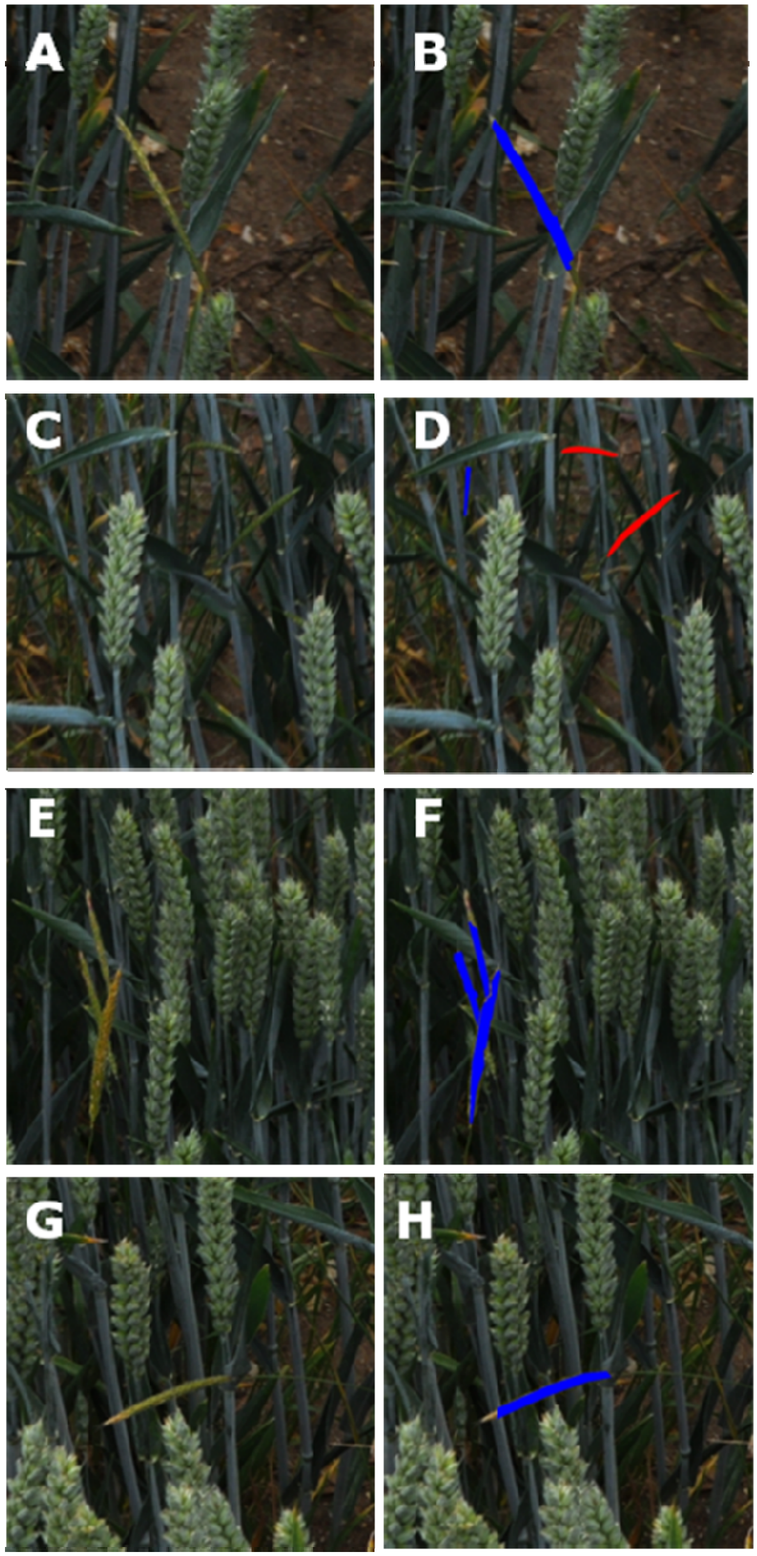


Figure 18. Detection of black-grass by machine vision at high densities. Original images (A,C) and the images (B,D) with black-grass heads either correctly classified (blue) or incorrectly *not* classified (red). White objects are false positives which were *misclassified* as black-grass. In A, the arrow points to a flowering head, which is classified correctly in B.

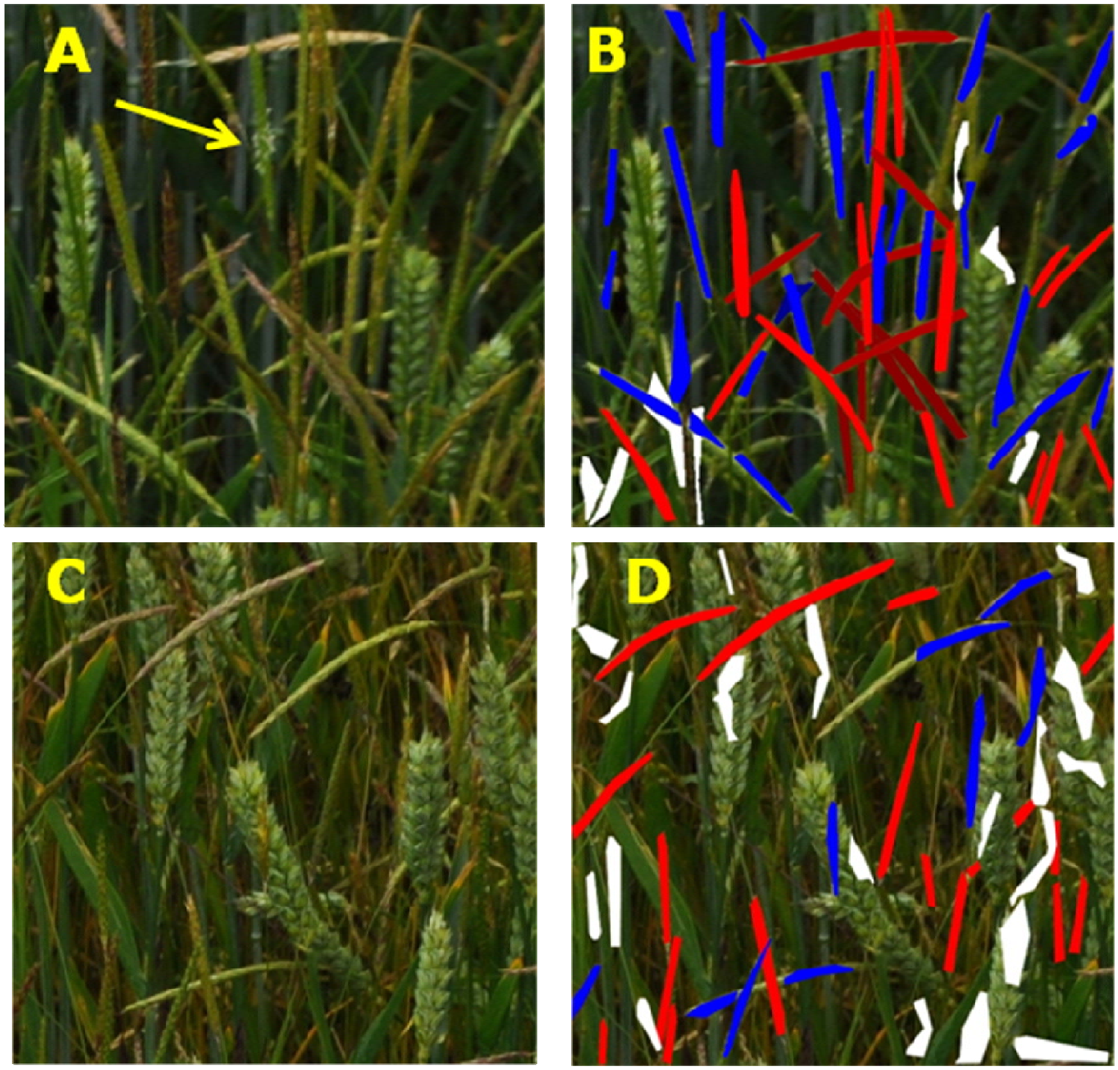
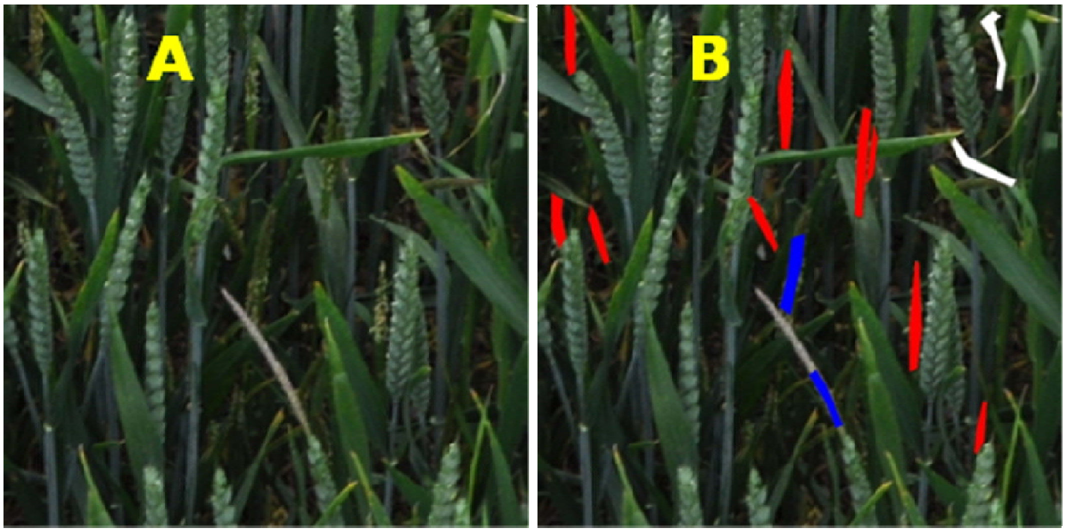


Figure 19. Detection of dark black-grass heads in the background of an image.

Key: A) original image and the images (B) with objects correctly classified by the machine vision system as black-grass (blue) or or else not classified (red) or misclassified (white objects).



3.3.5 Optimal Times for Weed Detection

Times when identification is likely to be possible using an image capture / machine vision system such as that developed in this project are indicated for weeds likely to occur in patches and for which site specific weed control would be useful are listed in Table 7. Images have been captured for all the species listed (and others not listed) but algorithm development has focused on black-grass at wheat GS 59-71. The basis on which autumn-germinating seedlings of black-grass might be geo-located and classified as grass weeds would be in inter-rows before canopy closure as illustrated in Figure 3 given pixel size of 0.3 mm (section 3.3.1.3, pixel size specification).

Table 7. Optimal detection times for weeds in patches by the machine vision system developed in this project. Key: ☑ Detection and identification possible; ☒ Detection and/or identification difficult for reason given.

• **Black grass**:	
• **T3: Spike emergence until seed fall (May/June)**	☑
• Harvest: wispy mass of stems	☒
• Seedlings images captured October and December	as 'grass' weeds
• **Wild oat:**	
• T3: Panicle emergence	☑ In progress
• Harvest	☑ Pending
• **Barren brome:**	
• T3: Spike emergence until seed fall (May/June)	☑ In progress
• Harvest: difficult due to lodging	☒
• Seedlings images captured October and December	No images
• **Cleavers**:	
• T3 and harvest	Few images
• Seedlings images captured December 2009	Looks promising
• **Thistles**:	
• Harvest infestations	Looks promising

3.3.6 Objective 3: Demonstration of Concept of Weed Mapping based on Detection of Weeds in Geo-referenced Photographs.

The technology and software required for this part of the project were largely developed for the previous weed-mapping project. In this report, therefore, it is only necessary to show that images captured using the machine vision system will be adequate for creation of weed maps. There are two parts to the question:

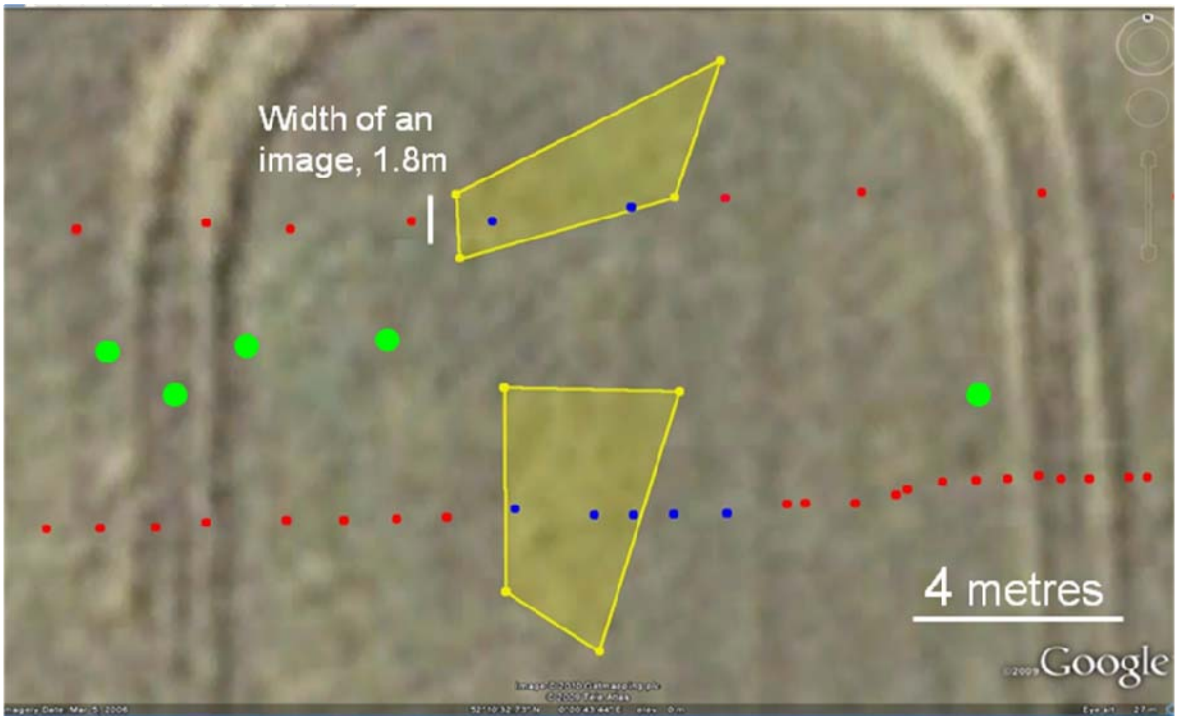
1. Can we geo-reference weeds?
2. Can we create a weed map from geo-referenced images?

This project differs from others in one important respect, namely that the aim is to produce maps of weeds in one season so that farmers and agronomists have high quality information on which to base their control strategy in a following season. Although not required for this project and difficult to achieve in the short-timescale of this project, farmers and agronomists will be particularly interested in the answer to a third question:

3. Are patches of uncontrolled weeds in one season correlated with infestations in the next?

Figure 20. Geo-referenced image locations plotted as point references on a Google Earth Satellite image of part of a field.

Large green dots represent geo-location of images captured at T3 in June 2009. No wild-oats were present in these images. The small red and blue dots are geo-locations of images captured at harvest in August 2009 using a small plot combine (Figure 1D), the blue and red representing the presence or absence, respectively, of wild-oats in the images. The yellow quadrilaterals represent the boundaries of two manually-mapped wild-oat patches immediately prior to harvest in August 2009.

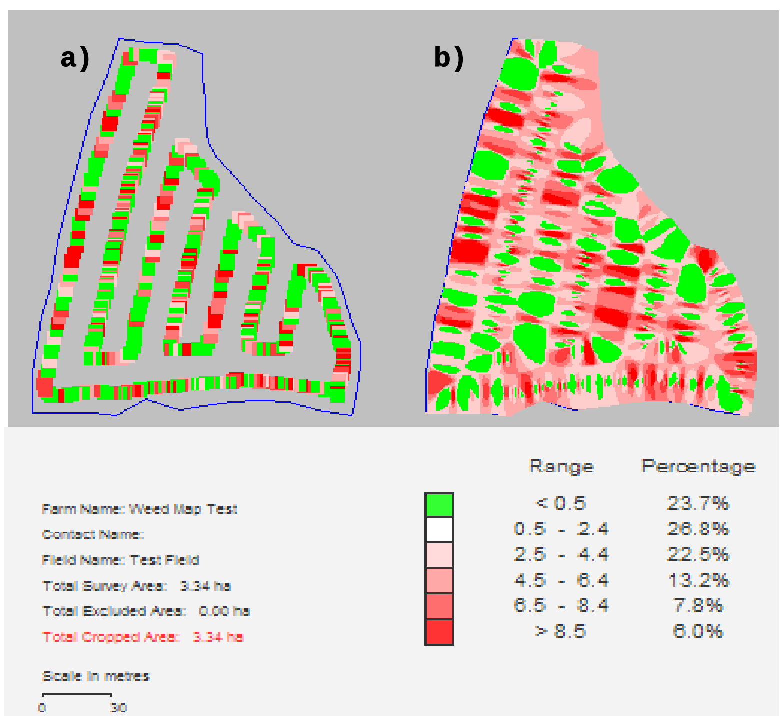


Superimposing image geo-locations on a Google map provides a reasonable visual correlation of GPS locations of weeds in images captured by machine vision with actual location in-field according to the Garmin handheld GPS receiver (

Figure **20**). Acknowledging that much more extensive validation is needed, the implication of this preliminary analysis is that an acceptable accuracy of geo-referencing by machine vision is achievable.

Given weed densities in images at known geo-locations, we have confirmed that data from the machine vision software in this project are compatible with and can be imported into Patchwork Office software and algorithms developed in the previous weed mapping project in order to create weed maps. Two examples to confirm the process are provided for proof of concept only (Figure 21). Interpolation can be used to estimate densities between image locations (Figure 21b) although interpolation would not necessarily be acceptable in a commercial version.

Figure 21. Partial screen shots of maps of weed densities in arbitrary units a) at image geo-locations and b) interpolated over field. Maps created with arbitrary data for a field used in this project. Maps produced by Nick Walters of Patchwork Technology Ltd., using Patchwork Office software and algorithms developed in the previous weed mapping project.



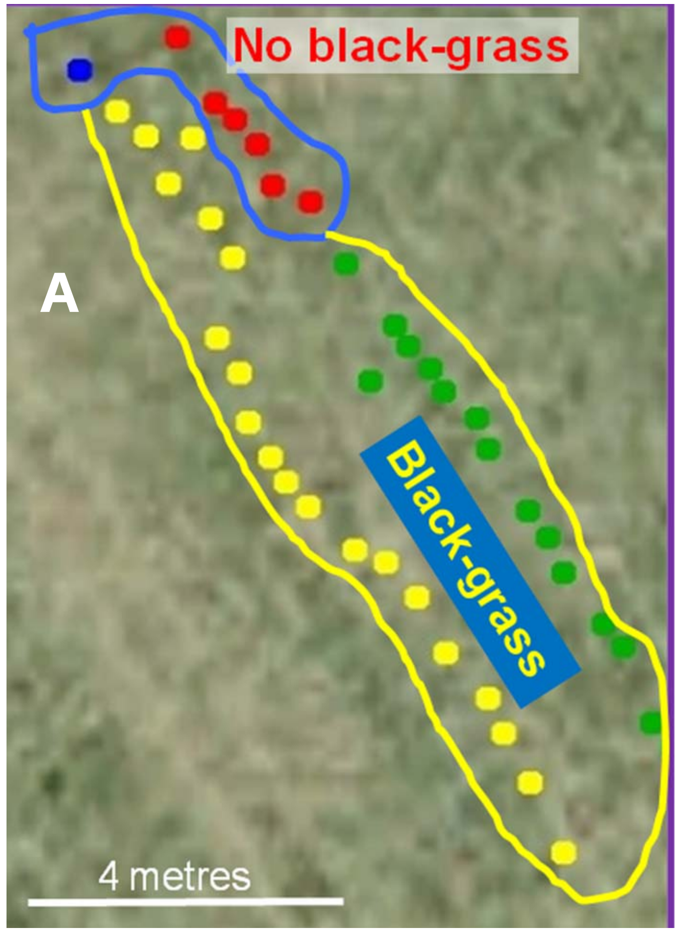
Finally, were geo-referenced patches of uncontrolled weeds in one season correlated with infestations in the next? Again only a preliminary analysis is provided given the time-scale of the project. When images were captured at approximately identical geo-references in wheat in June 2009 and in winter beans in December 2009, there is a good coincidence of locations where the images contained patches of uncontrolled, seed-producing black-grass heads in winter wheat at T3 in June 2009 with seedlings in winter beans in December 2009 (Figure 22) suggesting that mapping uncontrolled black-grass in one season could be a good indicator of a high likelihood of a black-grass infestation in the following season.

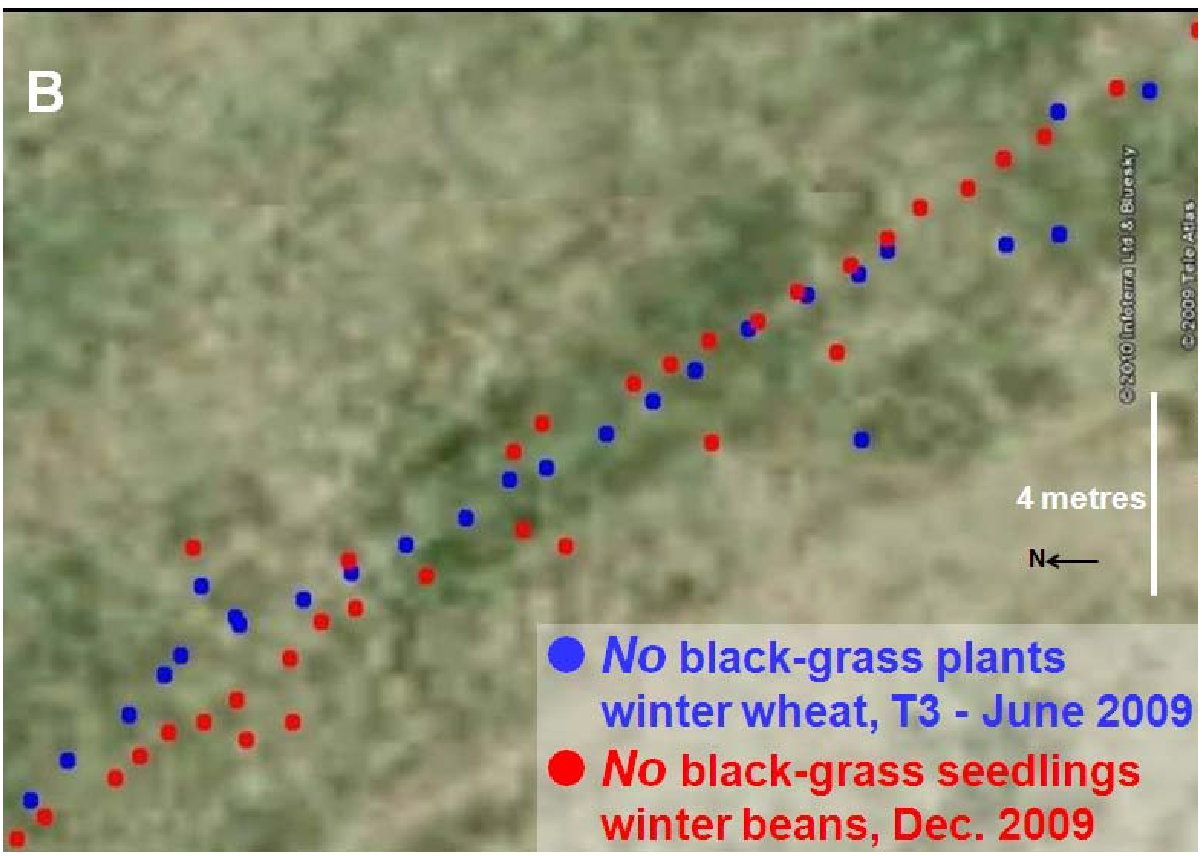
Figure 22. Geo-referenced image locations of two field visits, Phillimore Farms, near Reading, showing parts of the same field where black-grass was A) present or B) absent with inflorescences at T3 in wheat in June 2009 or as seedlings in winter beans in December 2009. Image capture locations are shown on a Google Earth satellite image.

Key:

Blackgrass **present** in June 2009 (heads ●) and in December 2009 (seedlings ●)

Blackgrass **absent** in June 2009





3.3.7 Discussion and Conclusions

3.3.7.1 Overview

The project has established the feasibility of the concept of automatically collecting images on farm machinery in the field, analyzing those images and implementing software sufficient to support the development of a prototype automatic weed mapping system. Images were of insufficient quality when captured at 20 km h^{-1}, but images captured at slower speeds could be used for image processing. It is considered that this performance is fit for purpose as spraying should not be carried out at 20 km h^{-1}.

3.3.7.2 System Hardware

A preliminary image collection system was put together using a laptop computer, GPS receiver and high-end digital camera. Brackets and other attachment methods were used to fit the camera to existing farm vehicles to collect images.

3.3.7.3 Image Collection

Primarily, the field images analysed were for T3 and harvest of wheat. Samples of other images were collected at other growth stages and allowed deduction of optimal times for weed identification. Sufficient images were obtained to support image requirements analysis and for the development of algorithms and software for detection of black-grass in wheat. Preliminary analyses for wild-oats and barren brome and for seedlings of black-grass have not been included in this report apart from the use of the excessive green filter on black-grass seedlings (Figure 3).

3.3.7.4 Image Analysis

The analysis of field images concentrated on issues of resolution, geometry, frame rate, platform motion and field coverage. As a result of this effort the baseline parameters for a prototype image collection system have been established and are reported above. We established a functional relationship between a camera CCD size, lens field of view and the minimum object feature size necessary to support object detection and classification functions.

3.3.7.5 Algorithm Definition and Design

We determined a methodology for image processing that successfully segments, detects and classifies black-grass (and wheat) plants in complex environments. This methodology uses a series of bit-level operations on the entire image to separate objects and regions of interest from the background clutter. It reduces the bitmap images to a list of features and syntactic elements that define candidate objects' shape and location in the image. These syntactic elements include a skeleton following the main axis of the object and a contour that defines its border. A preliminary classifier has been developed that can differentiate black-grass from the background clutter with a consistently high probability (Figure 16) so that false negatives can be avoided (Table 6). The research needed to reduce the numbers of false positives will be described later.

Existing software from Patchwork Technology for the generation of a weed map from geotagged images was evaluated to show that our weed detection software was compatible with the mapping software (Figure 21).

3.3.7.6 Software Development

The algorithms described have been implemented and tested on a desktop computer. The emphasis in the project has been to establish functional performance of the detection and identification algorithms and to determine the computational loads anticipated for large-scale processing.

3.3.8 Research needed to bring to a Pre-commercial System

3.3.8.1 Overview

An important objective in applying for a follow-on project would be to develop and test a pre-commercial prototype weed mapping system, which could be rapidly taken into production. Many of the elements of the system that have been tested as a proof of concept could be integrated into a prototype design.

3.3.8.2 System Hardware

The prototype system will need to be enclosed in an attachable housing and may provide its own power if necessary. A major goal will be to resolve manufacturing methods and technology (MM&T) to support a commercial version of the system.

Prototype Image Capture System. During the current project important lessons were learned about the necessary camera resolution, required image collection and storage rates, and system field-of-regard coverage. The emphasis in future research can be on the transition from a research project to a practical system to support commercial agriculture.

Automated Machine Vision Processing and Archival. A major task for future work will be to implement a database management system (DBMS) to store and manage weed maps. This DBMS needs to interface with the machine vision software with a goal of automating the process as much as possible. As part of this automation process a means of monitoring the performance through visual inspection of selected images should be provided. Also the software should be able to tag for human evaluation any images for which computed classification probabilities are low. In other words if the machine vision system is experiencing unexpected behaviour (number, size or shape of candidate objects or out of normal range features) it will be able to tag and set aside those images for review by the farmer or agronomist.

Universal Mounting and Alignment Technique. Another important task for commercial development will be to establish a mechanism for attaching and aligning the image capture system to the various types of farm vehicles that will carry it. This issue is related to our ability to geo-locate objects in the images. In order to perform this function, it is essential to know and control the orientation of the image capture system with respect to the carrier platform. One technique under consideration is to have quick-release mounting brackets permanently attached to each farm vehicle so that when the image capture system is re-attached no additional calibration of alignment is required.

3.3.8.3 Image Collection and Analysis

Images need to be collected from a much wider range of environments and in different seasons to fill in the gaps for some growth stages (especially T2) and a wider range of weed species and in different crops.

Alternative Image Collection Methods. Now that the feasibility of machine detection and classification of weeds in field images has been demonstrated for high resolution images, it is important to determine the most cost-effective means of collecting and storing images of sufficient quality to support the machine vision system. One alternative of particular interest is the use of high-resolution progressive scan digital video cameras. The higher frame rates, shorter integration times and larger storage capacities make these cameras an attractive alternative to single frame SLR cameras such as the D90. An issue to be resolved is, whether video images can be extracted from the stream and whether these frames can be time-referenced to a GPS data stream with sufficient accuracy to achieve a geo-positioning precision sufficient to support weed mapping.

Image Analysis. Most of the necessary image analysis for black-grass in wheat at T3 has been completed in this project. Similar studies are required for other weed and crop types, as well as other growth stages.

3.3.8.4 Data Correlation Studies

One of the fundamental assumptions of this weed mapping study is that weed patches of the target species persist over several growing seasons. In follow-on research, this property should be exploited to refine the weed map knowledge base for the fields monitored over several years. During planting or possibly at harvest, regions of the field infested with weeds will be covered with newly emerging weed plants. The specific type of weed may be very difficult or impossible to determine for these images. Since this project has demonstrated that it is possible to identify black-grass and other weed types growing in wheat, it will be useful in future research to evaluate correlation of weed data extracted from image sets collected at different times during the growing season. We postulate that such data correlation will achieve a higher probability of weed type identification and more precisely defined weed patch boundaries. For this reason, temporal correlation studies are an important topic further research in order to improve the confidence of farmers in the system.

It is also important to demonstrate that patches associated with failure of control in one season are correlated with seedling emergence in the next. A preliminary examination of the season-to-season correlation was shown in section 3.3.5.

3.3.8.5 Adaptive Probability Detection

The ability to detect grass weeds in grain fields is a challenging task. Any methods that increase the probability of detection, decrease the number of false negative or false positive errors, or that reduce the computational load should be seriously considered. In fields in which it has been established that weed patches have been present in previous years, there is the opportunity to implement an adaptive probability detection model that can take into account the *a priori* probability of the presence of weeds as a function of geo-location.

Local Adaptive Histograms. A couple of shortcomings of the segmentation algorithms that have been developed were noted. Some black-grass heads located in the background of an image have a lower HSV value signal compared with the majority of black-grass heads in an image. This low value signal causes such heads to be lost in segmentation using HSV value bands. The second issue is where the HSV hue and value signals in areas of an image immediately adjacent to a black-grass head are similar to the HSV signal of the black-grass. Such a head then becomes part of the image ‘background’ and so is eliminated during segmentation.

Similar problems occur in medical applications such as bone fracture detection or analysis of electron micrographs. Techniques like Local Histogram Equalisation have been applied to mitigate the problem in medicine. The processing maximises the difference in intensity in a small areas of an image rather than throughout the image as applied in normal equalisation algorithms. The algorithm proposed is the Contrast Limited Adaptive Histogram Equalization (CLAHE) (Saalfeld, 2009), as this technique may make it possible to increase the number of less conspicuous heads that are segmented and classified.

3.3.8.6 Algorithm Definition and Design

Future research needs to emphasise the development and improvement of object classifiers (both parametric e.g. PCA, Mahalanobis distance and non-parametric e.g. the Set-Intersection Method). Semantic methods for identification of weed types will be used in which general and expert knowledge is used to analyze the relative locations and distributions of the candidate objects. These methods will help improve object identification and clutter rejection, and also reduce processing loads.

Pipelines and Classifiers for Plant Types. In this project our emphasis was on black-grass in wheat, with most algorithm development devoted to T3. While image capture and algorithm development has been carried out for other growth stages and other weed species, additional work is still needed to generate a fully-functional classification system for these growth stages and weeds and so results are not presented in this report. The proven machine vision concept demonstrated for black-grass in wheat at T3 can, however, and indeed should be extended to a broader range of weed species.

Expert and General Knowledge Rule Base. An *ad hoc* set of rules for algorithm design was used to support the development of object detection and classification algorithms. In future research, the opportunity should be taken to formalize and codify an expert knowledge rule base with a comprehensive set of physical characteristics for each species that could be detected by the cameras. In addition the general knowledge rule base should be extended and validated to ensure that all available contextual information is being exploited and that no erroneous or misleading assumptions are included. These rule bases will support the algorithm refinement process for the machine vision system.

3.3.8.7 Software Development

Research is needed to increase the processing speed and automation of the overall weed mapping process. Specific tasks will include (1) the automatic processing of multiple field images in a single program execution; (2) the automatic categorization of weed map data into a database management system; (3) the development of visualization tools to display and evaluate weed maps at various image scales.

3.3.8.8 Geo-Referenced Object Location

Another important task will be to implement and demonstrate software for the determination of the absolute position of weeds and other plants in images. The issue is that a particular plant in an image taken at a specific time is in a position different from the position of the GPS receiver. The solution to this problem is one of applying the proper geometric transformations to each image position based on the carrier platform's position and direction of motion (heading) at the time the image was captured. The feasibility of this process has been demonstrated in this project, but a study is needed to determine the precision of the method and, if necessary, improve its performance through multiple sample averaging or image stitching techniques.

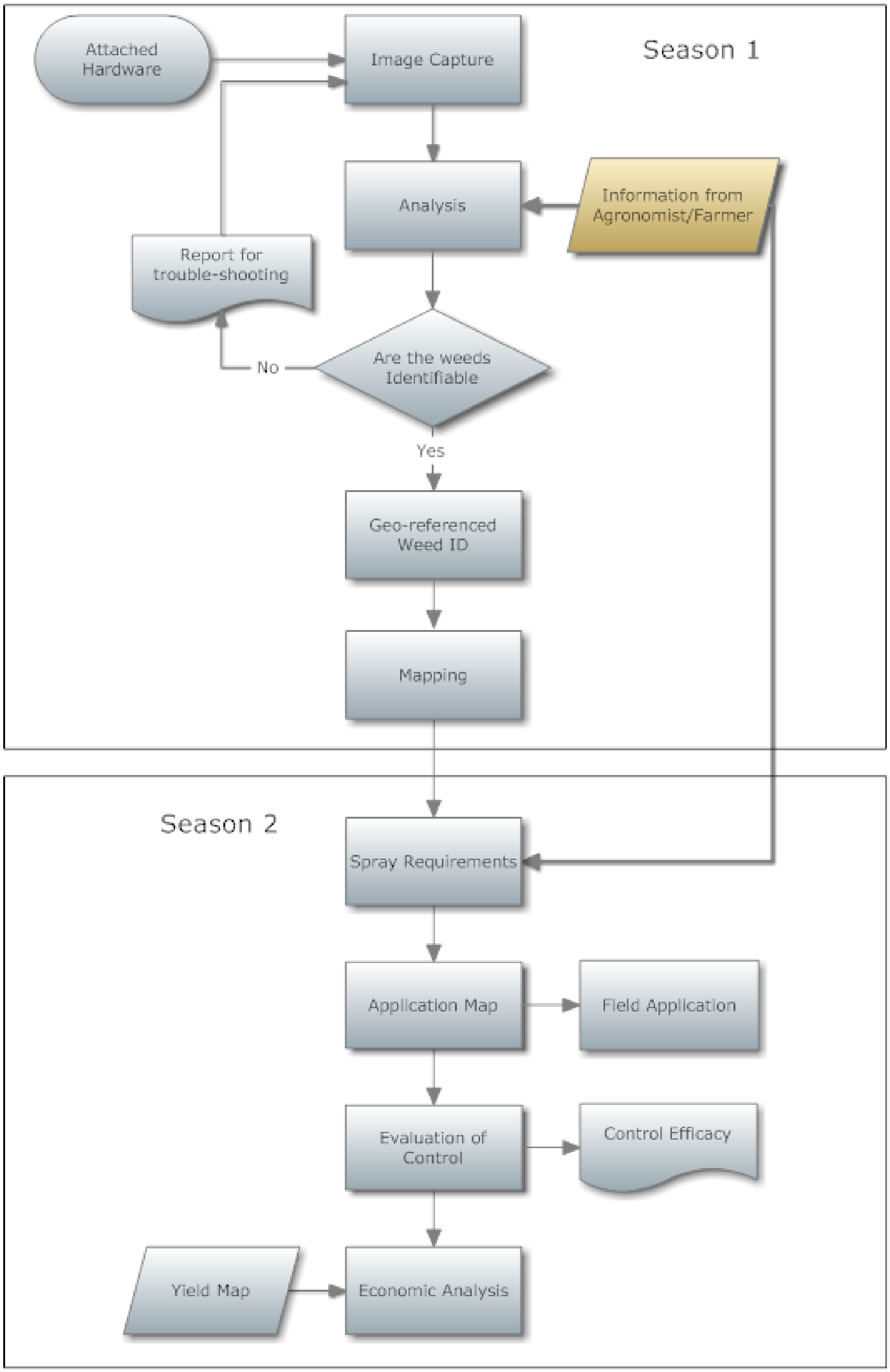
3.3.8.9 Other applications

It will be obvious that there are broader applications of the weed mapping system than weed control. Extension to other weeds, which perhaps occur more randomly in fields and tend not to form patches, would be useful especially where they are either rare or of proven biodiversity value (Wilson *et al.,* 1999; Gibbons *et al.,* 2006). In such cases, the decision might be to leave small patches of such weeds untreated in order to preserve or enhance the biodiversity value of the field.

The image analysis system not only identifies weeds, but also crops so that the two can be distinguished. Applications for crop management can also be envisaged if maps of, for example, crop plant populations or ear density were generated.

Figure 23. System concept of precision weed control based on weed mapping in the first season and control in the next.

In practice, mapping may continue in the second and subsequent seasons to update the weed map and improve its accuracy. The system aims to automate the drudgery of weed mapping but expert, local knowledge from agronomists and farmers is indispensable, especially as highlighted.



3.3.9 Conclusion

Scope for implementing site specific weed control is therefore considerable and the system proposed in section 3.7 is at the leading edge of technology for offline image processing. The difficult task of identifying weeds at late crop growth stages has been achieved for the first time ever as far as we are aware.

The possibility therefore exists of a system which both utilises the expert knowledge of farmers and agronomists of the problem weeds in their fields (**Figure 23**) and then informs them of the precise locations of patches of these weeds and of where problems of infestations may arise in future seasons. They may then use these weed maps to produce treatment maps (**Figure 23**) capable of controlling variable rate sprayers, which will not only control weeds at lower cost and with lower herbicide inputs, but also, by mapping late in the season, will alert them to areas where weed control has failed and there is perhaps potential development of herbicide resistance.

3.3.9.1 Key Take-Home Messages for HGCA Levy Payers

The concept of automated mapping of uncontrolled black-grass in winter wheat has been proven in principle and should be developed both as an aid to site specific weed management and detection of potential herbicide resistance.

Funding is, however, required to make the system of use to levy-payers. Specifically research is needed as follows:

- Algorithm development to ensure algorithms are adaptive to different conditions found in UK and in different seasons, in different crops, to different weed species and at different crop and weed growth stages;
- Software development to link maps created at different times in order to improve confidence of users in the maps and to confirm inter-seasonal correlations of infestations on a field scale;
- Application testing in the field combined with economic analysis; and
- Development of a pre-commercial system as in **Figure 23** capable of scanning whole fields as an integrated, cab-mounted system unit including portable camera(s), GPS receiver and single board computer.

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