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The Use of Spectral Properties for Weed Detection and Identification – A Review

Scott D. Noble, Ralph B. Brown

School of Engineering, University of Guelph, Guelph, ON. N1G 2W1.

Email of corresponding author: snoble@uoguelph.ca

Trever G. Crowe

Department of Agricultural and Bioresource Engineering, University of Saskatchewan. 57 Campus Drive, Saskatoon, SK S7N 5A9

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Abstract:

Many approaches to weed detection and identification have been reported in the literature. Most of these approaches can be categorized as being spatial, based on plant morphology, spectral, based on the light reflected from the plant surfaces, and hybrids of the two. This paper is a review of spectral techniques that have been reported. This includes equipment for data acquisition, the use of high and low spectral resolution data, a brief discussion of the use of spectral properties for image segmentation, and the use of spectral data for species discrimination. A summary of factors that have been found to be significant under real-world conditions and directions for future research is also presented.

Keywords. **machine vision, spectral signatures, colour segmentation, precision agriculture, review**

The Use of Spectral Properties for Weed Detection and Identification – A Review

S. D. Noble[1], R. B. Brown[1] and T. G. Crowe[2]

[1]School of Engineering, University of Guelph. Guelph, ON N1G 2W1. Email of corresponding author *snoble@uoguelph.ca*

[2]Department of Agricultural and Bioresource Engineering, University of Saskatchewan. 57 Campus Drive, Saskatoon, SK S7N 5A9

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Introduction

The potential for using plant reflectance spectra in precision agriculture has been the focus of many researchers for some time. Applications that have been investigated include nutrient management, monitoring yield quantity and quality, and the detection of weeds for selective herbicide application. The scope of this paper is restricted to those approaches to weed detection and classification that are based primarily on the reflectance and spectral properties of the species. Methods that make significant use of spatial relationships between pixels, and spectral or colour textures are not the focus of this review. An overview of the spectral properties of green plants is provided, followed by a presentation of the major types of apparatus used for data acquisition. Methods for using the data are presented. The paper concludes with discussions of considerations for field applications and suggested directions for foundational research.

Reflectance properties of plants

The general reflectance properties of green vegetation have been well established, and are illustrated in Figure 1. Reflectance is low in the visible range (approximately 400-750 nm), with a peak in the green region centred at approximately 550 nm, and lower reflectance in the adjacent blue and red regions. Chlorophyll and other pigments are primarily responsible for the response in the visible region. The transition to the NIR region is characterized by a sharp increase in reflectance, referred to as the red edge. Water dominates the response in the NIR region. The band between 800 and 1350 nm is relatively flat and known as the NIR plateau. The plateau region transmits light readily (Gates et al. 1965; Myers et al. 1966; Noble and Crowe 2001), which may have implications for the use of NIR

measurements taken under field conditions. This plateau is followed by a lower reflectance region due to major water absorption bands at 1450 and 1950 nm, with regions of increased reflectance in between (Noble 2002).

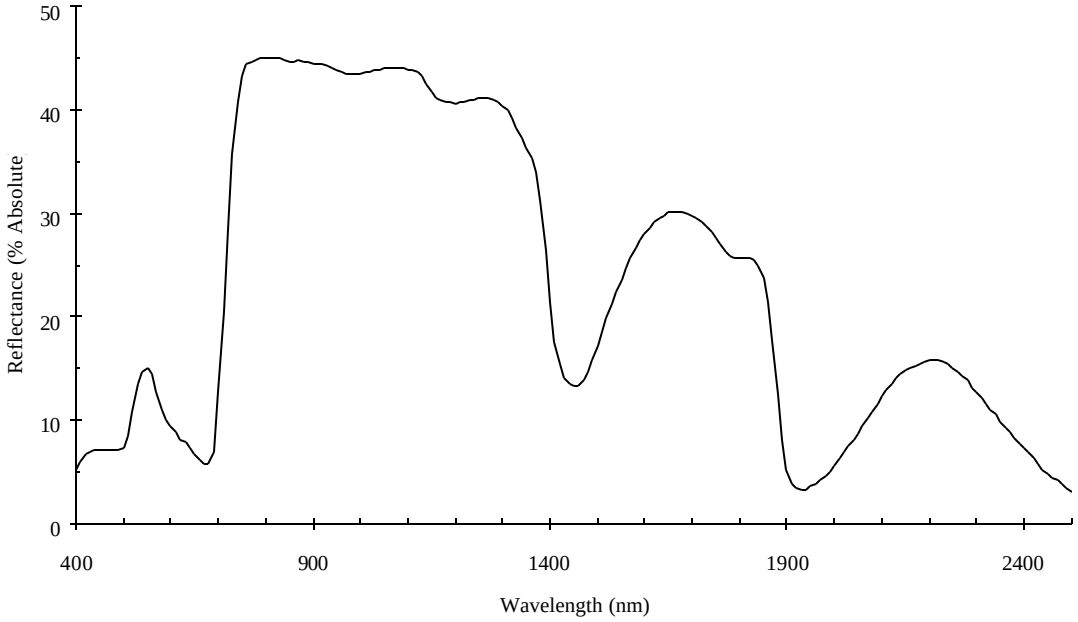

Figure 1. Typical leaf reflectance curve between 400 and 2500 nm (Noble 2002).

Documenting the reflectance properties of various crop and weed species has been the subject of numerous studies (ex. Allen et al. 1970; Billings and Morris 1951; Everitt et al. 1986; Everitt and Richardson 1987; Gausman et al. 1969; Gausman and Allen 1973; Gausman et al. 1981; Gausman and Leamer 1981). Most studies of these types were concerned primarily with measuring reflectance values with a view to satellite or aerial remote sensing, and describing the relationship between leaf structure and leaf reflection. A review of factors affecting leaf reflectance was presented by Grant (1987). While several of these studies included some discussion of discrimination based on spectral features, studies generally lacked sufficient sample size for meaningful classification.

EQUIPMENT USED FOR NEAR-FIELD SPECTRAL STUDY OF WEEDS AND CROPS

To classify the equipment used for collecting spectral information about plants, two properties of the output produced by the apparatus will be used. The spectral resolution refers to the spectral bandwidth of the measurement. High spectral resolution indicates a narrow measurement bandwidth, thus enabling the system to resolve finer spectral features. In the following discussion, “high” and “low” spectral resolution are used qualitatively, with the boundary between the two defined as approximately 50 nm. Spatial resolution refers to the area over which individual measurements may be taken. High spatial resolution systems, typically found in imaging applications, may have a pixel resolution on the order of a few millimetres or smaller. Detectors in low spatial resolution systems integrate the light reflected from an area in excess of a few square centimetres, or take point measurements that are not in the context of measurements of the surrounding areas. As with spectral resolution, the boundary between the two is not clearly defined. In this discussion, systems will be generally classified as being either high or low spectral and/or spatial resolution.

Low spectral resolution systems typically use broadband filters, whether they are for high or low-spatial resolution work. These systems may be as simple as inexpensive filters over a photocell, or more complex filter and camera arrangements. The red, green, blue (RGB) system of colour cameras is typical of the latter. Note that by using narrow-bandwidth filters, these systems would become high-spectral resolution systems.

Spectrophotometers and spectroradiometers are typical of high spectral resolution systems with limited spatial resolution. These instruments are used to take point measurements, as opposed to an array of measurements as in an imaging system. Some of these systems are capable of measuring reflected light from a small target area, and may be considered to have high-spatial resolution, albeit impractical for field applications.

Several techniques for acquiring high-spectral, high-spatial resolution data are in current use. These are used in the context of spectral imaging, the data from which may be thought of three dimensionally as a cube, known as data cubes or hyper cubes. The cubes are made up of layers of either spectral or spatial data, depending on the acquisition method. If a filter-based system is used, the cube consists of layers of spatial data collected at different wavelengths. Alternatively, each layer may represent the spectra of points along a line, with consecutive layers containing the information for sequentially scanned lines. The number of layers depends on either the number of spectral bands used or the number of lines scanned.

The simplest method for acquiring high-spectral resolution data is by using a camera with a series of narrow bandpass filters. An example of this is the filter wheel and high frame rate camera used by Achalakul and Taylor (2001). This design allowed for up to 12 spectral bands, determined by the filters chosen and loaded into the wheel. For this type of apparatus, each consecutive image could be taken at a different wavelength, up to the maximum number of filters. If the target is moving, this type of sequential acquisition may not be appropriate, depending on the speed of the object and the frame rate of the camera.

A second filter-based approach allows multiple images, each in a separate spectral band, to be collected simultaneously on a single imaging device. After entering through a common aperture, the incoming light is split, with each stream being directed through a different filter and projected on a separate region of the image plane. This type of device was used by Throop et al. (2000) to detect defects on apples on a conveyor system, and Edner et al. (1994) for fluorescence lidar (light detection and ranging) imaging of vegetation. In some applications, the optical filter approach is also implemented using multiple cameras (ex. Baron et al. 2002; Crowe and Delwiche 1996), or a single device employing prisms and filters to direct components of the light onto different imaging sensors (Wilson 2002). This approach is practical in situations where the desired wavelengths are well defined prior to acquiring data, wavelengths are limited in number, and filters are readily available. If motion is a factor, it may also be more appropriate than techniques that acquire spectral data sequentially. While filters may be changed in some systems, this would be inconvenient if many spectral bands were needed, or if the desired filter wavelength or bandwidth were unknown or unavailable.

A second class of high spectral and high spatial resolution apparatuses uses a tuneable filter instead of a series of fixed-wavelength optical filters. These tuneable filters are actually diffractive devices whose passband is adjusted by driving the filter at different frequencies, causing the material to behave as a variable-wavelength transmission grating. These may be acousto-optic tuneable filters (AOTF) or liquid-crystal tuneable filters (LCTF). Both are generally limited to a responsive range of one octave of drive frequencies, which appears to roughly translate into a one-octave optical bandwidth (i.e. lower wavelength to two times the lower wavelength). Coupled with a camera, the tuneable filter is driven to a different wavelength for each successive image, resulting in an image cube containing an

image for each desired wavelength. Some time, approximately 20μs for an AOTF (Brimrose 1999), is required between each image for re-tuning the filter to the next wavelength.

These tuneable filter-based imagers have been used by a number of researchers investigating plant identification and stress analysis. An overview of some general applications of the LCTF was presented by Gat (1998). Thai et al. (1997) developed an LCTF-based system for detecting herbicide stress levels in plants. Haralson et al. (1997) used an AOTF in their study of using spectral properties to distinguish between weeds and crops using high-resolution spectral imaging.

A third type of system is based on the imaging spectrograph. These systems are described as line-scan or pushbroom devices. A line from the target area is projected through diffractive optics and onto the imaging array. One axis of the image represents the spatial position along the line being scanned, while the other axis represents the spectral information. The other spatial dimension is varied in the line-scan approach, either by moving the scanning system, using a scanning mirror, or moving the object being scanned. Scanning through consecutive rows of the scene collects data for the entire image. Because all spectral data for a given line are captured simultaneously, the system may capture data for scenes in motion, so long as the rate and direction of travel are known. Commercially available imaging spectrographs have been used for defect detection in apples (Kim et al. 2001), and studies on distinguishing between weeds and crop species (Borregaard et al. 2000; Vrindts and De Baerdemaeker 2000). The development of a low-cost spectrograph-camera unit and associated weed-crop discrimination results were briefly reported by Feyaerts and van Gool (2001), and described in more detail by Ramon et al. (2002).

Use of low spectral resolution data in image processing for weed detection

The use of low spectral-resolution data (i.e. spectral bandwidth greater than 50 nm) to extract information from images for weed detection is well established in practice. This information is usually in the form of red, green, and blue (RGB) colour coordinates, with the frequent addition of a near-infrared (NIR) measurement. This information is most often used to segment the green plant material from the soil and crop residue in the image, reducing the number of pixels to be processed in subsequent stages of the analysis and classification. Using broadband measurements for distinguishing between species has also been investigated by a number of researchers.

COLOUR BASED SEGMENTATION

Some means of segmenting the input into vegetation and background regions is almost universally done as a first step in the process of distinguishing plant species. By performing this segmentation, the number of pixels to be analyzed is reduced. In some applications, such as greenness-triggered spraying systems (ex. Detectspray), or estimating biomass or canopy coverage (Baron et al. 2002), it may be the main processing step. Taking advantage of the dramatic change in the reflective response of green plants at the red edge, some variation in a red/NIR ratio is generally used. Thresholds for this ratio are set, and pixels classified accordingly (Baron et al. 2002; Vrindts and De Baerdemaeker 2000). A more complex version of the simple ratio is the normalized-difference vegetation index (NDVI), which has the advantage of normalizing the data to account for some intensity variation (Criner et al. 1999; Feyaerts and van Gool 2001). Chappron et al. (1999) found the L, a, b colour system to yield the best results for segmenting, using the ‘a’ component plus an infrared measurement. In cases where only RGB data were available, colour indices have been used to good effect (El-Faki et al. 2000; Tian and Slaughter 1998)

Other methods of segmenting plant objects from an image have been explored. Borregaard et al. (2000) found that ratio and index methods were inadequate due to shadow and intermediate (i.e. spectrally mixed) pixels. Reflectance measures at 678 and 758 nm were used for segmentation. The investigators found that linear discriminant analysis was able to classify pixels as being plant, soil, shadow or intermediate with higher reliability than ratios or indices.

LOW SPECTRAL RESOLUTION DATA FOR CLASSIFICATION

After using a spectroradiometer to obtain high-spectral resolution data of plant canopies, Brown et al. (1994) used this information to select gelatine filters for further image collection. Filter passbands were centred on 440, 530, 650 and 730 nm. Images of weed patches in corn were taken from heights of eight meters from a cherry picker, and approximately 600 m from an airplane. The corresponding spatial resolutions were 15 X 15 mm and 150 X 150 mm. The Bhattacharya distance was used as a measure of separability between soil, quackgrass, foxtail, milkweed and corn classes, based on the multi-spectral image data. Results were described as promising, with the coarser spatial resolution data yielding better classification.

Wang et al. (2001) reported on the development of a spectral-based weed sensor. The system used six phototransistors, five of which were fitted with bandpass filters. The filters were centred at 496, 546, 614, 679 and 752 nm. Filters were inexpensive thin films whose bandwidths were not specified in the paper. The sensor was positioned above and in-front of the specimen, at a 45° angle from the ground. Four colour indices based on these wavelengths were used as input to a discriminant function classifier. Indices were constructed based on the apparent differences of the slope between a given pair of wavelengths for different leaves, stems and soil. Wheat was correctly classified 83% of the time, and weeds were correctly identified 62.5% of the time, given sufficient plant density. The main advantages of this type of system are the relative simplicity and potentially low cost of implementation. However, changing the spectral properties of a sensor of this type after it was built would be difficult, and moving to narrowband filters would affect the cost significantly.

A number of other researchers have used broadband colour, such as RGB, in conjunction with measures of spatial texture for plant classification (Shearer and Holmes 1990; Shropshire and Glas 1992; Zhang and Chaisattapagon 1995; Burks et al. 2000). This technique requires the measurement of the spatial relationship between pixels in an image, and is therefore not within intended scope of this paper.

NON-IMAGING HIGH SPECTRAL RESOLUTION

Mack et al. (1978) used a spectroradiometer to collect spectral data of wheat cultivars in the field, between the stages of early heading and being fully ripe, at a spectral resolution of one nanometre. The data were reduced to a spectral resolution of 10 nm for analysis. Generally, the spectral regions around 480, 680 and 1450 nm were found to be most useful for distinguishing the crops, while wavelengths from the NIR plateau region, 880 to 1200 nm, were not useful.

Several more recent projects have involved the collection of high-spectral resolution data from plant leaves early in the season with the purpose of finding optimal wavelengths and analysis methods to be applied to further system development. In order to select the most appropriate filters for multi-spectral imaging, Brown et al. (1994) used a spectroradiometer to collect reflectance spectra between 400 and 900 nm of several weed species in no-till corn fields under natural lighting. Separability of the data was assessed using an F-test and separation of means (Duncan's multiple range test). Wang et al. (2001) used a diode-array spectrometer to collect reflectance spectra to aid in the development of a

spectral sensor for weed detection. Weeds were placed on a highly reflective diffuse reflectance material and the reflectance of leaves and stems were measured between 400 and 1700 nm. Data were converted into light absorbance using the a= log(1/r) transformation where 'a' equalled absorbance and 'r' equalled reflectance, both of which were functions of wavelength. Wavelengths for discriminating between species and soil (496, 546, 614, 679 and 752 nm) were selected based on category contrast methods and the availability of inexpensive colour filters for prototyping.

Vrindts and De Baerdemaeker (1997) used a spectrophotometer to collect leaf reflectance spectra from potato, beet, corn (maize), a variety of weed species, primarily dicots, and soil. Measurements were taken between 200 and 2000 nm. Data were averaged to yield one data point per 10 nm for analysis. The data were randomly separated into separate training and test sets. Features were selected using stepwise discriminant analysis, and classification using discriminant functions.

Discrimination between beets, weeds (primarily broadleaf), and soil was achieved with 0% error in the testing set using wavebands centred on 1925 and 1715 nm, becoming more robust with the addition of the waveband at 755nm. Corn and barnyard grass (cockspur), were grouped together, and were best separated from weed and soil classes using wavebands centred on 1285, 455, 355 and 685 nm. Corn and barnyard grass were separated with 0% error using wavebands at 1085, 645, and 695 nm. Potato, weed, and soil were separated using wavebands at 765, 515 and 1935 nm with only 1.5% error.

Moshou et al. (2001) reported testing a neural-network based classifier against a number of other classifiers, using the data of Vrindts and De Baerdemaeker (1997). The proposed neural network was reported to yield better results than all other methods tested, however, the original discriminant function classifiers used by Vrindts and De Baerdemaeker (1997) were not included in the comparison. The original classification of the data appeared to have classification results equal to or better than the neural network approach.

In a similarly structured study to that of Vrindts and De Baerdemaeker (1997), Noble (2002) studied the ability of spectral data to distinguish between six crop and weed species common to western Canada: wheat (*Triticum aestivum*), Argentine canola (*Brassica napus* L.), pea (*Pisum sativum* L.), wild oat (*Avena fatua* L.), wild buckwheat (*Polygonum convolvulus* L. a.k.a. black bindweed), and Canada thistle (*Cirsium arvense* (L.) Scop.). Infinite reflectance data were used as classifier inputs, calculated via a technique using reflectance measurements against contrasting backgrounds (Major et al. 1993). The best six-class classifier used wavebands centred at 420, 360, 680, 1930 and 2110 nm, with a 93.4% correct classification rate. The majority of the error was contributed by confusion between wheat and wild oat, with 15% error for each of these classes. A classifier for wheat and wild oat alone achieved 100% correct classification using wavebands at 410, 390, 350, 400 and 370 nm. The best classification between the four broadleaf species was 98.4%, achieved using wavebands at 1710, 1920, 430, and 680 nm. Two-way classification between grassy and broadleaf species was done with greater than 99% accuracy using measurements at only two wavebands, 730 and 540 nm. This was the only classifier for which a waveband from the green region of the spectrum was selected by the discriminant analysis.

While direct comparisons cannot be made between the results presented by Vrindts and De Baerdemaeker (1997) and Noble (2002) due to differences in species used and the way they were grouped, some wavebands do appear similar. Both studies found that wavebands near 1920 and 1715 nm were selected for cases involving broadleaf separation. Wavebands in the red absorption trough (at approximately 680 nm) and on the red edge (at approximately 730 nm) were also reported in both studies. Wavebands from the green portion of the spectrum were reported in both studies, but infrequently. Both studies report the selection of wavebands in the UV spectral region. Plant pigments are known to fluoresce under UV light (Lichtenhaler and Rinderle 1988), so it is possible that the selection of this waveband actually represents a fluorescence feature. The spectrophotometers used

were unable to distinguish reflected light from a fluorescent reaction under normal operation. UV induced fluorescence spectroscopy may be a potential tool for plant identification if it can be transferred to the field, as suggested by Chappelle et al. (1984a,b)

Vrindts et al. (1999) used a spectrum analyzer with an effective field of view two centimetres in diameter to measure the reflectance of crop and weed plants in soil, in contrast to measuring the reflectance of excised leaves (Vrindts and De Baerdemaeker 1997; Noble 2002). Crops used were sugarbeet (*Beta vulgaris*), maize (*Zea mays*, a.k.a. corn), annual mercury (*Mercurialis annua*). Weeds were Canada thistle (*Cirsium arvense*), lambsquarter (*Chenopodium album*), chickweed (*Stellaria media*), redshank (*Polygonum persicaria*), black nightshade (*Solanum nigrum*), mayweed (*Matricaria chamomilla*) and grass (*Poa annua*). Reflectance measurements were converted into wavelength ratios by dividing the reflectance at each waveband by the reflectance at each of six characteristic points of the reflectance curve. Separate testing sets were not used for validation of the classifiers. Using discriminant function classifiers, perfect classification between corn and weeds was achieved with six wavelength ratios (705/555, 725/815, 1935/1455, 915/555, 1475/555, 1535/555), and between sugarbeet and weeds with four wavelength ratios (545/1665, 1875/1455, 1705/555, 1085/815). Ratios containing wavelengths at 1935 and 1705 nm were close to values found by both Vrindts and De Baerdemaeker (1997), and Noble (2002). The reflection at 1085 was selected in Vrindts and De Baerdemaeker (1997) and Vrindts et al. (1999).

In these studies, reflectivity was measured over a range of wavelengths from the UV well into the NIR region. From the results, it appears that some information for species discrimination may be found well into the NIR region at approximately 1920 and 1715 nm. These wavelengths are well beyond the upper sensitivity of standard CCD cameras, which is typically 1000 nm or less. It was also observed that wavelengths on the NIR plateau might not hold as much discriminating power as has been suggested elsewhere (Borregaard et al. 2000). Vrindts and collaborators (1997, 1999) found only a few wavelengths in this region, and Noble (2002) found none. Reflectivity in the green region of the spectrum also appeared to be less significant than one would intuitively expect based on human vision.

IMAGING HIGH-SPECTRAL RESOLUTION

A study using an imaging spectrograph was conducted by Borregaard et al. (2000), in the 660 to 1060 nm spectral range. This corresponded to the spectral region containing the red chlorophyll absorption band, the red/NIR transition edge, and the first section of the NIR plateau. This range was selected on the assertion that more important information was contained in the NIR region than the visible. This was generally the opposite of the findings of Vrindts and collaborators (1997, 1999) and Noble (2002), who found the majority of their features outside of this range.

Data were collected at a spectral resolution of two nanometers, and reduced to a resolution of eight nanometres for classification. The pixel size was 1.5 by 6 mm. As a first step, pixels were classified as plant, soil, shadow, or intermediate (mixed) using the measurements at 678 and 758 nm and linear discriminant analysis. The ability of the data to discriminate between each of the two crop species (potatoes and sugarbeet), and a conglomerate weed class was tested. Species in the weed class were black bindweed (*Polygonum convolvulus;* a.k.a. wild buckwheat), fools parsley (*Aethusa cynapium*), and fat hen (*Chenopodium album*; a.k.a common lambsquarters). Plants used in the study were grown outdoors in portable boxes, to approximately the four-leaf stage. Twenty spectra were chosen from each species for training, and 16-20 from each for testing.

It was reported that intra-species reflectance variation was greater than the differences between class means, requiring the use of multiple features for classification. Four different classification schemes were used: linear discriminant analysis (LDA), quadratic discriminant analysis (QDA),

principal component analysis with soft independent modeling of class analogy (PCA/SIMCA), and partial least-squares regression (PLS). Features selected for the discriminant function classifiers were measurements at 694, 970, 856, 686, 726, 897, and 978 nm. Best performance for the four-way classifiers (sugarbeet vs. three weed types) was 79%, achieved by the PLS classifier using seven latent variables. For the binary classifiers (single crop vs. lumped weed class), only the LDA and QDA approaches were used. Both achieved 94% correct classification for potato vs. weeds. For classifying sugarbeet and weeds, LDA had an 87% success rate, and the QDA an 89% success rate. Overall, the worst performance was from the four-class sugarbeet vs. all weeds classifier using the LDA approach, at 60%.

Haralson et al. (1997) used an unsupervised, competitive, artificial neural network (ANN) to classify species in images obtained with an AOTF and camera. Data cubes of several crop and weed species were obtained between 500 and 1000 nm, and some between 650 and 850 nm under outdoor, natural lighting conditions. After using red-NIR thresholds to segment the vegetation from the background, a single waveband was used as input to binary classifiers for distinguishing between pairs of species: 630 nm for soybean and grass, and soybean and smartweed, 730 nm for soybean and lambsquarter, and 710 nm for soybean and volunteer corn. The training data were also used to test the classifier, the reasoning being that because the ANN was unsupervised, the data could be recycled in this way. Correct weed classification rates ranged from 45% to 89%. Overall, classification rates were higher for crops, with 96% for soybean and grass, 84% for soybean and smartweed, and 81% for soybean and volunteer corn. The relationship between canopy height and the angle of the incident light was cited as an important factor in classifier performance. While testing with independent data should be done, some of these classification results are interesting, considering only one wavelength was used for classification. Independent testing data would give a better indication of the value of this approach.

Vrindts and De Baerdemaeker (2000) collected field data using an imaging spectrograph over the spectral range of 485 to 815 nm. Data were collected for corn (*Zea mays*) and sugarbeet (*Beta vulgaris*) at the three to five leaf stage. Weeds present in the scans were common lambsquarters (*Chenopodium album* L.), annual meadow-grass (*Poa annua* L.), purple dead-nettle (*Laminum purpureum* L.), mouse-eared cress (*Arabidopsis thaliana* L.), shepherd's purse (*Capsella bursa-pastoris* Med.), dandelion (*Taraxacum sp.*), annual mercury (*Mercurialis annua* L.), chickweed (*Stellaria media* Vill.), annual sow-thistle (*Sonchus oleraceus* L.), burning nettle (*Urtica urens* L., a.k.a. stinging nettle, small nettle) and ground ivy (*Glecoma hederacea* L.). Spatial resolution for analysis was 20 mm by 4 mm, with a spectral resolution of 2.1 nm. Data were collected outdoors, and no correction for daylight variation was applied. After segmenting vegetation from the soil, stepwise discriminant analysis was used to select wavelength features, and a binary discriminant function classifier using *a-priori* probabilities was developed for classification between each crop and a conglomerate weed class. The data were split into separate training and testing sets. Sugarbeet classifiers used up to 11 wavelength features (814.6, 801.4, 753, 713.5, 698.1, 522.1, 761.8 603.5, 764, 537.5, and 579.3 nm), and corn up to nine features (700.3, 511.1, 592.5, 484.4, 495.8, 671.7, 687.1, and 605.7). The best sugarbeet classification was 95% correct, with a corresponding weed classification rate of 84%. Corn identification results were poor, with 15% correct corn classification and 97% correct weed classification. The poor performance was attributed to very different illumination conditions for the testing set for corn. When using wavelength ratios, performance of the corn classifier improved to a high of 56% correct classification. The ratios were not able to completely correct for the variation in the quality of the light. It was suggested that a measure of incident radiation be used to convert the reflection values to reflectance ratios for more robust classification.

Feyaerts and van Gool (2001) developed a prototype low-cost spectrograph-based system, and tested it under natural lighting conditions. The system had a spectral resolution of 35 nm and range of 435 to 1000 nm. Plants were grown in the field, and were transplanted to the measurement area,

ensuring that the plants did not overlap or shadow each other. Plants had between four and six leaves. The sensor was positioned above the area to be scanned, and was moved forward at a constant speed. To compensate for varying, natural illumination, a reference object whose reflection spectra could be used as a standard was always in the instrument's field of view. Seventy plants of each species in the study were used. These were sugarbeet (*Beta vulgaris* L.), annual meadow-grass (*Poa annua* L.), narrow-leaf plantain (*Plantago lanceolata* L.), common chickweed (*Stellaria media* L.), common lambsquarters (*Chenopodium album* L.), and redshank (*Polygonum persicaria* L.). Vegetation and background pixels were segmented with a normalized difference vegetation index (NDVI) using reflectance at 760 and 660 nm. The feature set was chosen based on the optimal wavelength for each crop-weed pairing, using equation 1 as the measure of separability,

$$F_X^Y(\lambda) = \frac{\left|\overline{X}(\lambda) - \overline{Y}(\lambda)\right|}{\sqrt{s_X^2(\lambda) + s_Y^2(\lambda)}} \quad (1)$$

where $\overline{X}(\lambda)$ and $\overline{Y}(\lambda)$ are the mean reflectance for classes *X* and *Y*, and $s_X^2(\lambda)$ and $s_Y^2(\lambda)$ are the variances for classes *X* and *Y* respectively at wavelength λ. The wavelengths chosen were 441, 446, 459, 883, 924 and 988 nm. Four different classification schemes were tested: minimal distance classifiers, k-nearest neighbour, multi-layer neural network with non-linear mapping, and a CART classification tree. Overall, the results from the neural network classification between crop and weeds were highest, at 85.8%. However, this was only marginally higher than the minimal distance classifier using the Mahalanobis distance at 85.7%. Crop classification was poor compared to classification of weed species.

Considerations for the real world

As the various techniques for acquiring and applications for spectral plant discrimination are moved into the field and used under real-world conditions, several key factors appear to be critical for success: the nature of the lighting used, field conditions, and the spatial resolution of the detection system.

Illumination

The variable nature of natural lighting is a major factor that must be considered in applying weed detection technologies to the field. Vrindts and De Baerdemaeker (2000), for example, used an imaging spectrograph with uncontrolled natural lighting to distinguish sugarbeet and corn from weeds. The corn testing data were collected under different lighting conditions than the training data. Corn misclassification was on the order of 85% or greater. Using simple wavelength ratios to compensate for the variations in illumination reduced misclassification to a minimum of 44%, only marginally better than random selection. The authors noted that light correction was a necessity.

In a study of the "Detectspray" vegetation-activated sprayer, Blackshaw et al. (1998) found that adequate light intensity was not consistently present until 70 to 80 minutes after sunrise. El-Faki et al. (2000) investigated the effects of varying light intensity on colour-based classification of soil and redroot pigweed. Artificial lighting was used, with controlled intensity. It was found that while the raw red, green, and blue grey levels changed dramatically with incident light intensity, the resulting colour indices used varied only slightly. It was observed that not all of the changes were linear with respect to intensity, nor were the raw red, green, and blue curves parallel to one another. The method of controlling the light intensity was not indicated, leaving open the possibility that the spectral

characteristics of the illumination source may have also changed with the intensity. Regardless, the indices were able to compensate for changing light levels to a large degree.

Using transformations from colour co-ordinates, where individual colours have associated intensities, to a system where the intensity and the relative presence of each waveband are independent, may also compensate for varying intensity. Tian and Slaughter (1998) used a normalized RGB colour space in developing an environmentally adaptive segmentation algorithm to distinguish between plant and soil pixels. Each colour channel was normalized by dividing by the sum of the three channels. Tests were carried out under a range of natural lighting conditions. Using the normalized colour space was found to greatly improve performance over the non-normalized classifier. Moshou et al. (2001) used a similar approach for spectral data, where every point in each spectra was divided by the spectra norm. Steward and Tian (1999) noted that the normalized RGB colour space had unstable tendencies at low intensities. Thus, they opted for the IV_1V_2 coordinate system, where I was the intensity, and V_1 and V_2 formed a two-dimensional colour space. A transformation from RGB to HSI (hue, saturation, intensity) format has also been used to cancel intensity effects (Shearer and Holmes 1990; Burks et al. 2000) when using colour co-occurrence matrices for species discrimination. These latter transformations are more computationally demanding than the simple indices, but they do reduce the colour information from three dimensions with intensity, to two dimensions with intensity information separate.

In addition to the illumination intensity changing, changes in the quality of the illumination, or its spectral makeup, must also be considered. Natural lighting quality, as indicated by its colour temperature, may vary from dawn sunlight at 2000 K, to noon sunlight at 5400 K. Skylight may have colour temperatures as high as 18000 K, with the average combination of sunlight and skylight being 6500 K (Jacobson 1988). Changing cloud cover has been reported to alter visible and NIR measurements differently (Shropshire and Glas 1992; Baron et al. 2002). Changing light quality will affect the value of wavelength ratios if proper calibration and compensation are not applied. Colour indices and colour-space transformations appear to be able to compensate for intensity variation. However, they are unable to apply adequate corrections for changes in the spectral characteristics of the illumination source. A method of correcting for changes in intensity and spectral properties is to keep a reflectance target within the field of view of the instrument. Shropshire and Glas (1992) used a photographic grey card to manually set the desired aperture for each bandpass filter used. Automatic techniques have been used successfully by Feyaerts and van Gool (2001) and by Baron et al. (2002). In the latter case, a dark-level correction target was used in addition to a white target. A variation on this theme is to use a fibre-optic bundle to collect the downwelling radiation and directing it into the spectra separating optics (SPECIM 2002). This has the advantage of not having to place a standard target within the field of view, which could be awkward if used on moving equipment.

The direction and angle of light has also been noted to affect classification. Shropshire and Glas (1992) observed that, even under diffused outdoor lighting, intra-species variations were strongly influenced by leaf orientation relative to the light. A study using artificial illumination from banks of fluorescent tubes found that classifier performance was reduced if leaf orientation relative to the direction of incident light was not accounted for (Franz et al. 1991). In their study using an AOTF-based system, Haralson et al. (1997) found that better classification was achieved in a case where the weeds and soybeans were “flat” compared to other species and images studied, and therefore at a more desirable angle with respect to the incident light.

Whether the illumination is direct or diffuse is also a factor. Under direct lighting, reflections are more likely to have a strong specular component, resulting in hot spots. Borregaard et al. (2000) reported that diffuse lighting resulted in a spectrum with fewer visually distinct features.

Field conditions

Blackshaw et al. (1998) found that the ability of the Detectspray system to detect small weeds was impaired by stubble 0.3 m high, and also if the stubble density was greater than 150 stalks per square meter. It has also been speculated that the underlying litter underneath the plant canopy may influence reflectance readings in the NIR region due to the high light transmission by leaves in these wavelengths (Noble and Crowe 2001). This phenomenon is familiar to the remote sensing community, but has received relatively little attention among researchers working on ground-level weed detection.

The maturity of the crop canopy may also be a factor in the ability of the system to detect weeds. If the canopy is too mature it may hide weeds even in the inter-row space. Thompson et al. (1990) suggested that, based on their observations with winter wheat, crop canopy coverage would be such that only 5% of small weeds could be detected one month after crop emergence.

Several researchers have noted the effect of soil moisture content on plant/soil segmentation. Criner et al. (1999), studying area coverage detection thresholds for bindweed, noted that soil moisture had an effect on the ability of the system to determine if bindweed was present. This system used a NDVI threshold approach, and it was noted that the ability to monitor background reflectance and adjust the thresholds accordingly would likely improve performance. El-Faki et al. (2000), using an RGB colour camera in a study of moisture content effects on classification, found that the grey level in each of the three colour-bands changed dramatically with soil moisture. However, it was found that changes in colour-index values were relatively insignificant. After several morphological post-processing steps to remove disjoint noise pixels, it was observed that soil moisture content had virtually no effect on classification between soil and redroot pigweed pixels.

Resolution

Further considerations are the optimum spatial and spectral resolutions at which spectral data should be acquired for weed detection and species discrimination. Brown et al. (1994) found that the coarser resolution of 150 X 150 mm yielded better classification results than the finer 15 X 15 mm resolution. This was attributed to a reduction of local variation by integrating over a larger area. Borregaard et al. (2000) indicated that the spatial resolution of their line-imaging system was fine enough to measure reflectance from small areas of the plant, although not adequate for reflectance measurements to be taken from very small elements such as cotyledons. In this case, extended segmentation was used to reduce the local variability in the data by eliminating the mixed-spectra pixels. Criner et al. (1999) found that their simple reflectance-corrected NDVI index could reliably detect the presence of vegetation (bindweed) if the vegetation covered even as little as 6% of the field of view for this low-spatial resolution system. In contrast, El-Faki et al. (2000), trying to measure the reflectance of redroot pigweed stems, found that best results were obtained using a spatial resolution of 0.52 X 0.42 mm. The optimum spatial resolution would appear to depend on the spectral homogeneity of the object, its size, and the desired detection limits.

To date, no comprehensive study relating the spectral resolution of input data to species discrimination has been found in the literature.

SPECTRAL VARIATION AND MIXING

Other technical challenges aside, there are two realities that are impediments to using spectral information alone in a robust classifier. These are the similar basic spectral responses exhibited by all green plants, and the inherent variability that comes with biological entities. Zwiggelaar (1998), interpreting weed spectral data published by Brown et al. (1994), observed significant overlap between

the spectra of different species, based on the standard deviation from the mean. This variability was cause to question the potential robustness of classifiers based on spectral features. For classifiers to work reliably, they must be able to distinguish relatively subtle differences in spectra, and variability is an impediment to that. The worst-case scenario of variability in a sample presumes that deviation from the spectral mean at each wavelength is independent of the variation found at other wavelengths. Independent variation would obscure shape and slope patterns in a given spectral signature. However, the variations are probably not independent of each other. Table 1 shows the correlation coefficients for reflectance measurements at 12 wavelengths for 40 canola leaves, based on absolute reflectance measurements from Noble (2002). While some correlations are low, none are strongly negative, meaning that for a given sample, measurements at different wavelengths tend to vary in the same direction (i.e. above or below) the mean value for each wavelength. This example is not definitive, and can only be applied to samples of similar maturity that have experienced similar growth conditions. However, it does suggest that variability is not random across wavelengths for a given sample, and that the underlying characteristics may be preserved in spite of the inherent variation, even if the deviation from the population norm is large. This has also been borne out by the number of studies that have presented promising classification results, some under field conditions. Understanding the variability and finding means of correcting for it will be key to making these promising classifiers practical.

Table 1: Correlation coefficients at 100 nm intervals for canola (*Brassica napus* L.) from 350 to 1450 nm, based on R_s training set data from Noble (2002).

	Wavelength (nm)											
	350	*450*	*550*	*650*	*750*	*850*	*950*	*1050*	*1150*	*1250*	*1350*	*1450*
350	1.00											
450	0.82	1.00										
550	0.25	0.53	1.00									
650	0.66	0.92	0.72	1.00								
750	-0.04	0.38	0.68	0.55	1.00							
850	-0.02	0.40	0.62	0.56	0.99	1.00						
950	-0.04	0.37	0.59	0.49	0.97	0.97	1.00					
1050	-0.05	0.36	0.58	0.49	0.97	0.97	1.00	1.00				
1150	-0.04	0.33	0.50	0.41	0.90	0.90	0.97	0.97	1.00			
1250	-0.03	0.33	0.47	0.39	0.86	0.87	0.95	0.95	1.00	1.00		
1350	0.00	0.28	0.33	0.28	0.69	0.69	0.83	0.82	0.93	0.96	1.00	
1450	0.26	0.42	0.23	0.38	0.43	0.45	0.59	0.58	0.73	0.78	0.89	1.00

Related to this variability, Price (1994) presented some examples of mistakes that may be easily made when working with spectral data. These were related to the within-species variability, inter-species spectral similarity, and the effect of spectral mixing. Spectral mixing occurs in situations where multiple specimens are within a single detection area, resulting in their superposition. Examples of within-species variability for corn were presented, as found in Biehl et al. (1984). The spectra shown were quite different in some wavebands, presumably due to differences in maturity or growing conditions. A robust classifier must be able to accommodate such variations, or the variations must be due to some factor beyond the required scope of the classifier. For example, seedling corn and corn in tassel would not reasonably occur at the same time in the same field, and so having a single classifier that can identify both as corn may not have any practical value. The opposite case of this is when spectra from different species appear very similar, as was illustrated by overlaying selected sunflower, alfalfa, and corn spectra. A similar case, wheat and wild oat, both at the four to five-leaf stage, was observed by Noble (2002). Even between these visually similar species, sufficient difference was found to classify these species with high accuracy. This was done under well-controlled lab conditions, and this type of classification needs to be tested under field conditions. In the third case, Price (1994)

presented a situation where the weighted linear sum of the spectra from two species produced a mixed spectrum that was virtually indistinguishable from that of a third species. While the examples presented by Price were carefully selected, the point that these phenomenons can occur is correct. The extent to which they may apply in a given situation, such as how they may affect the required spectral or spatial resolution, must be considered for the resulting classifier to be reliable.

POTENTIAL RESEARCH DIRECTIONS

On balance, the research results to date indicate that spectral information could, at the very least, provide important information for plant species classification. Based on the research published, there are several areas in which more study is required, and others where a re-evaluation of the problem may be warranted. These relate to the bandwidths selected, the selection of wavebands, the required spatial resolution and lighting.

To date, no study has systematically examined the role of bandwidth in classifier performance. Studies have been done with either wide or narrow bands, but a direct comparison has not been done. A study in which different bandwidths can be selected may provide useful information. Borregaard et al. (2000), Vrindts and De Baerdemaeker (2000), Feyaerts and van Gool (2001) and Noble (2002) all reported classifiers containing multiple narrowband features in essentially the same portion of the spectrum. Allowing the training procedure to select from wide and narrow bandwidths may provide some indication of whether fine spectral detail was being resolved, or if the classifier was simply adding weight to a portion of the spectrum by adding multiple, virtually identical wavebands.

The problem of finding the most appropriate waveband centre frequencies has been given far more attention than bandwidth, but consensus is limited. Results from Vrindts and De Baerdemaeker (1997) and Noble (2002) suggest that wavebands at approximately 1715 and 1920 nm may be useful for species discrimination, particularly for broadleaf species. However, these wavelengths are beyond the range of most readily available imaging sensors. Photocells may be an inexpensive alternative if lower spatial resolution can be used. Wavelengths in the upper UV portion of the spectrum have been found useful when studied. Their use and the potential of using fluorescence information should be investigated, even though methods for practically utilizing these tools in real-time weed detection are not immediately available. There does appear to be some consensus on the value of wavelengths from the red chlorophyll absorption trough, blue region and the red edge portions of the spectrum. Selecting a standard set of wavelengths for species discrimination may not be possible, however systematic study may narrow the field. To this point the selection of species, particularly weeds, appears to have been ad hoc with artificial, albeit pragmatic, distinctions made between crops and weeds. Rather than dividing species as crop and weed, a better understanding of how to distinguish species may be obtained by dividing and studying along family lines. A series of comprehensive inter- and intra-family discrimination studies may provide more definitive and predictive results than a series of unconnected, prescriptive studies of species particular to localized regions.

The optimum spatial resolution is dependent on the size of the object that is being identified and the nature of the identification. There is a difference in the spatial resolution required for detecting the presence of a plant and identifying what plant it is. If the resolution is too low, the object cannot be resolved, though it may make up a large enough component of the measured spectrum to make its presence known. If the resolution is too high, finer structures are resolved and there is less homogeneity in the measured spectra. The potential for multi-resolution systems should be investigated. Low-resolution data, requiring less sophisticated hardware and less computational power, could be used for rapid analysis of large targets and to detect the presence of smaller potential targets. If required, higher resolution equipment could then be used more efficiently.

Finally, some investigation of artificial lighting for weed detection and/or species discrimination is required. Natural lighting is most convenient for fieldwork, but it is highly variable and not always reliable. Diffuse broadband illumination with uniform intensity would eliminate many of the problems experienced with natural light (e.g. bi-directional reflectance, variable intensity and colour temperature), and would also open up the possibility of having autonomous equipment working at night.

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