WEEDS DETECTION BY GROUND-LEVEL HYPERSPECTRAL IMAGING

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ABSTRACT

Weed control of grass and broadleaf is commonly performed by applying selective herbicides homogeneously all over the field. Applying the herbicide only where needed has economical and environmental benefits. Combining remote sensing tools and techniques with precision agriculture concept has the potential to automatically locate and identify weeds. The objective of this work is to detect grasses and broadleaf weeds among cereal as well as broadleaf crops by spectroscopy. Leaf and canopy spectral relative reflectance values of three targets: crop (wheat and chickpea); grass weeds (GW); and broadleaf weeds (BLW) were obtained by field spectrometer. Leaf spectral classifications for botanical genera as well as category were almost perfect (99%). Canopy spectral classification for targets was accurate (95%) in homogeneous field of view (FOV). Within the critical period for weeds control, accurate classification was achieved for target in heterogeneous FOV, providing applicative herbicide implementation. Hyperspectral camera was selected to continue this study. The properties of the camera should improve the ability to separate spectrally between targets by applying high spatial resolution.

Keywords: Remote Sensing, Hyperspectral, Classification, Weeds detection.

INTRODUCTION

Site specific weeds control

Weeds are plants that grow in a place they are not wanted, and where they may cause a disturbance. In agriculture, weeds can cause severe damage to crops by: reducing crop yield and quality due to competition for resources (i.e., water, sunlight, and minerals) (Pinter et al., 2003; Slaughter et al., 2008); harming crops by allelopathy (Moran et al., 2004); hosting diseases and insects; and disturbing tilling and harvesting (Monaco et al., 2002). Weeds developing resistance to herbicides is an increasing problem (Jones et al., 2005; Mallorysmith et al., 1990; Marshall and Moss, 2008) in Australia alone it is estimated to impose an additional annual cost of more than 1 billion dollars (Gibson et al., 2008). Weeds are the most acute pest in agriculture with estimated annual global damage of around 40 billion dollars per year (Monaco et al., 2002). In Australia and the USA alone the cost of managing agricultural weeds exceeds 30 billion dollars per year (Lawes and Wallace, 2008).

More than 60% of the pesticides developed all over the world are for weeds disinfest – herbicides (Monaco et al., 2002) therefore it is not surprising that herbicides are the most common pesticide found in ground water (Manh et al., 2001). Herbicides in general are an environmental hazard that might be directly or indirectly damaging flora and fauna as well as humans and therefore, in some countries, there are restrictions of the amount of herbicides applied per area unit (Biller, 1998; Slaughter et al., 2008; Timmermann et al., 2003). The increasing pesticide use regulations, consumers concerns, and a growing interest in organically produced foods limit the long-term acceptability of herbicide application (Slaughter et al., 2008).

In most cases, weeds distribution in the field is non-uniform and highly aggregated to patches of varying size or in stripes along the field borders (Gerhards and Christensen, 2003; Gerhards et al., 1997; Lamb and Brown, 2001; Moran et al., 2004; Slaughter et al., 2008; Vrindts et al., 2002; Weis et al., 2008). The common uniform application of herbicides determined for a field are based on last year's weed problems or information obtained from scouting field edges (Manh et al., 2001; Moran et al., 2004). Therefore, the amounts of herbicides applied can be reduced. Reduction in quantity of herbicides implemented can be beneficial economically for the farmers and consumers as well as environmentally and in some cases without diminishing weed control efficiency (Pinter et al., 2003; Slaughter et al., 2008; Weis et al., 2008). This reduction in amount of applied herbicides should be statistically lowering the probability of weeds to build resistance and allowing longer periods of efficiency for herbicides. Site specific weed control and management could significantly reduce the quantity of herbicide applied and by this effecting positively the environment and economy (Eddy et al., 2006; Gerhards and Christensen, 2003; Gerhards et al., 1997; Slaughter et al., 2008; Timmermann et al., 2003; Weis et al., 2008).

It is possible to reduce herbicides quantities by applying it only where the weeds are located (Lindquist et al., 1998). While applying site specific weed management in case of non-uniform weeds conditions the use of 11 to 90 percent of the herbicides can be avoided without affecting crop yield (Brown and

Steckler, 1995; Brown et al., 1994; Feyaerts and van Gool, 2001; Gerhards and Christensen, 2003; Johnson et al., 1995; Lindquist et al., 1998). Topography, drainage, soil type, and microclimate are some of the variables that are affecting weed distribution and competition with crops, resulting in significant variation in weed spatial patterns in a specific field as well as in between fields (Moran et al., 2004), emphasizing the need to site specific weed management.

Site specific weed management can be implemented in one of two ways: real time concept – weed on-the-go identification and spraying or hoeing are executed successively; mapping concept – weeds are identified and mapped prior to herbicide application (Gerhards et al., 1997; Weis et al., 2008). Weeds detection and identification in real time can be performed by remote sensing methods that up to this stage are mainly based on the shape of plant leaves in early growing stages or the discrimination between soil and vegetation in the cases of pre-emergence of the crop or between the crop rows (Alchanatis et al., 2005; Moran et al., 1997; Slaughter et al., 2008). Remote sensing techniques can provide fast and cost-effective mapping of weed populations while such manual procedure for large areas is not practical (Hamouz et al., 2008; Zwiggelaar, 1998). Remote sensing applications can also allow better spatial as well as spectral methods for early and late season weed detection and site specific management (Alchanatis et al., 2005; Moran et al., 2004; Zwiggelaar, 1998).

Spectral separation of crop and weeds

The number of studies where classification at ground level of plant species have been tested over multiple growing seasons as well as different crops is very limited and the management of post-emergence herbicides based on spectral separation between crop and weeds is to be studied more (Moran et al., 1997; Slaughter et al., 2008; Vrindts et al., 2002; Zwiggelaar, 1998). Zwiggelaar (1998) mentions in his review that using selected wavelengths for the discrimination between crops and weeds in a row environment has not been shown so far and imaging in a limited number of wavelengths might not be sufficient. In order to distinguish spectrally between crop and weeds the first step is obtaining continuous spectra of only the plant for each species, this can be done by high spatial and spectral resolutions (Vrindts et al., 2002), concluding the need to employ relative reflectance values in order to classify crops and weeds and to minimize the different lighting conditions affect on the spectral data. Biewer et al. (2009) are recommending the implementation of linear spectral unmixing as a method for non-destructive assessment of plant species proportion in mixed plots as well as the combination of field spectroscopy and digital imaging. This combination can be expressed by hyperspectral ground level scanned imagery including the VNIR spectral regions.

The internal structure of a dicotyledonous leaf (e.g., broadleaved) contains relatively more spongy mesophyll tissue properties than a monocotyledonous leaf (e.g., grasses) (Raven et al., 2005). Therefore, a dicotyledonous leaf has relatively more air spaces among the cells resulting a higher reflectance in the NIR region than a monocotyledonous leaf of the same thickness and age (Gausman, 1985). The red-edge region, which is the slope appearing in spectral reflectance (relative reflectance values) of plants connecting the red (R) and NIR regions, is an important element in plant species separation and therefore it is potentially essential for weed – crop separation (Shapira, 2009; Smith and Blackshaw, 2003; Vrindts et al., 2002).

Eddy et al. (2008) evaluated spectral discrimination between single crop/weed combinations, grasses as well as broadleaves, by ground level hyperspectral sensor with the range of 400 to 1000 nm, divided to 60 bands, resulting in 10 nm spectral resolution. The images were obtained in early growth stages, until 28 days after seeding (DAS) and the data were analyzed by relative reflectance values. The classification is resulting high ability to separate the combinations. The last two dates resulted better classification than the earlier. Shapira (2009) is presenting high classification ability between crop and weeds, grasses as well as broadleaves, in the 25 to 40 days after emergence (DAE) that is the most critical period for weeds control in wheat fields.

Combining hyperspectral resolution with high spatial resolution, on ground level, can lead to high spectral as well as spatial separation abilities between crop and weeds. Such images can provide data in high spectral as well as spatial resolutions. Reflectance at high spatial resolution of specific targets (e.g., crops and weeds species, soil, shaded vegetation as well as soil) can supply pure spectra of endmembers contained on canopy scale to allow the ability to separate crops from weeds as well as better understanding of the canopy scale reflectance. Both scales leaf (also sub-leaf) and canopy, can be obtained by the same outdoor hyperspectral ground level image so the possibility of different environmental conditions is inconsiderable and the variations between lab and field measurements are avoided. The high spectral resolution data can be analyzed as entire spectra or be resampled to known operative or future satellites. Vegetation and Environmental New micro Spacecraft (VENμS) is a future satellite with 12 bands in the VNIR region, including 4 red-edge bands, with spatial resolution of 5.3 m, revisit time of 2 days with the same viewing angle, swath of 27 km and tilting capability of up to 30° along and across track. VENμS has a unique combination of properties and therefore potentially it can be a very powerful tool for site-specific weed management and other precision agricultural applications.

This work is mainly focusing on data obtained by the ASD FieldSpec Pro FR spectrometer with additional preliminary data obtained by a hyperspectral camera.

METHODOLOGY

Field work and data analysis obtained by spectrometer

Field measurements were performed on wheat and chickpea crops. The measurements and sampling were conducted in the winters of 2006-7 (2007) and 2007-8 (2008) at the Gilat Research Center (31°21'N, 34°40'E) and in Kibbutz Saad (31°28'N, 34°32'E) which are located in the northwest Negev, Israel.

The Analytical Spectral Devices (ASD) FieldSpec Pro FR spectrometer in the range of 400-2400 nm was used to spectrally measure plants in two levels: single leaf and a canopy of several plants, the measurements were carried out with the high intensity contact probe and the bare fiber adaptor, respectively. The canopy reflectance data were collected at solar noon ±1 h, under clear sky conditions with a bare fiber adaptor that was leveled in a nadir angle. The field of view (FOV) was 25° and the height of the probe was 1.4 m, so the instantaneous FOV was 0.3 m^2. Since canopy-spectral measurements were held in the early stage of crop and weed growths it can be assumed that change in the FOV between different measurements dates is negligible. Wheat or chickpea (crop), grass weeds (GW), broad leaf weeds (BLW), and soil were spectrally measured when the different spectral samples contained different proportions of these four components, which could have only one component or several components. The crop (wheat or chickpea), GW and BLW fractional vegetation cover (FC) was assessed for every spectral measurement.

The total amount of spectral samples was 1250, with the distribution of: wheat 550, chickpea 220, GW 170, and BLW 310. The samples were grouped differently according to the method of obtaining data (contact probe or bare fiber), days after crop emergence (DAE) as well as according to the four components proportions and relative coverage of vegetation in the FOV. All the groups were divided into two data sets: calibration and validation, 50% each. All data presented are for the validation data set.

There are two types of analysis: qualitative - classified to category and genera, in order to examine the ability to classify by spectral features; and quantitative - spectral measurements were coupled with FC assessments in order to examine the ability to predict it. The qualitative classification analyses were applied by the General Discrimination Analysis (GDA) tool of Statistica v.9 software. These classifications can be obtained by the most influencing wavelengths as well as by the entire spectra. The quantitative prediction analyses were applied by the Partial Least Squares Regression (PLSR) tool of the Unscrambler® v.9.1. software.

Spectral Camera HS

Data were also obtained in Gilat Research Center in the winters of 2008-09 (2009) and 2009-10 (2010) by the Spectral Camera HS (Specim) with 1600 pixel per line and 849 bands in the range of 400-1000 nm. The camera was placed 135 cm above a frame delimiting an area of 50 by 50 cm, the frame was at the canopy level as presented in Fig. 1. Relative coverage estimation of crop, BLW, GW, and soil was performed in the delimitated area located under the camera in each image. The images are converted to relative reflectance values by ENVI software. The process is based on the flat field method by white referencing to pressed and smoothed powder of barium sulfate ($BaSO_4$) positioned on the frame underneath the camera (Hatchell, 1999). By this experimental formation the images present very high spatial resolution of approximately 0.5 mm.

Data obtained by the ASD was already analyzed and the results are presented in this study. The data obtained by the Spectral Camera HS are still under preprocessing or in early stages of analysis therefore only preliminary results will be presented.

Fig. 1. Spectral Camera HS in a wheat field, focusing on the sensor point of view – in the frame: wheat, GW and BLW.

RESULTS AND DISCUSSION

Tables 1 and 2 presents high ability to classify pure leaf spectra sorted by genera and categories, respectively. These tables show results of classification applied for spectral measurements obtained by the contact probe (e.g., pure leaf spectral data). The classifications were applied for the entire spectra available by the ASD spectrometer. Table 1 presents almost perfect ability to classify different plant species, two crops (wheat and chickpea) as well as 13 weeds species (GW and BLW). Table 2 presents classification by category (wheat, chickpea, BLW and GW) for the same data set as Tab. 1 with additional 20 samples of plants that could be only identified as BLW or GW.

In comparison to other studies e.g., (Smith and Blackshaw, 2003) that discriminate the different specie by leaf spectra, this current study produced higher classification accuracy and a more extensive data set. When comparing the results of the two tables it can be concluded that the classification by category is as good as by genera. Gibson et al. (2004) as well as (Thorp and Tian, 2004) support the idea that site specific weed management does not require differentiation between weed species, but rather between crops and BLW and GW for reducing of herbicide usage. Tables 1 and 2 present the first step towards applicative tool for separation between crops and weeds GW as well as BLW.

Table 3 presents results for homogeneous samples based on continuous full spectral range and Tab. 4 shows results for samples with more than 30% vegetation coverage based on only 11 narrow bands selected by the Statistica software according to their importance to the GDA procedure. The 11 bands sorted by importance are 675, 715, 705, 745, 690, 875, 850, 1090, 750, 760, and 1070 nm. The first five wavelengths are in the red-edge region, another two red-edge bands also appear lower along the importance scale in between the only two bands of wavelengths longer than 900 nm. Therefore, the VENμS might be a good substitute for such implementations. Table 3 compared to Table 4 presents advantage for the 11 selected bands and a minimum of 30% vegetation coverage over the continuous spectra and 0 to 100 % vegetation coverage in classifying each of the four categories, by samples and the total classification

Table 1. Classification by GDA of pure leaf spectra by Genera, full spectral range.

Genera	Percent correct	Validation no. samples
Wheat	100	32
Chickpea	100	28
Hordeum	100	10
Hirschfeldia	100	20
Malva	100	40
Sinapis	96	24
Ipomoea	100	11
Avena	100	12
Solanum	100	11
Setaria	100	17
Silybum	100	11
Chrysanthemum	100	29
Sonchus	100	13
Lolium	100	9
Beta	100	14
Total	**99.6**	**281**

for each group by percent. It is assumed that the vegetation coverage is responsible for most of the difference between the two tables. However, an applicable air/spaceborne sensor have to deal with mixed spectra of crop, weeds and soil. When considering this factor, it seems that only large patches of weeds might be detected unless an unmixing of heterogeneous pixels will provide fractional coverage data.

When assuming that there are three herbicide application options: none, BLW, and GW. When embracing the concept that it does not matter if it is only weed, or a crop-weed mixture, the same treatment of selective herbicide should be applied. In other words: for area containing only wheat and soil no herbicide should be applied; for area with wheat and BLW or just BLW only BLW herbicide is applied; and for wheat and GW or just GW only GW herbicide is applied. Tab. 5 presents classification results for heterogeneous spectra with more than 5% vegetation coverage restricted to 25 to 40 DAE in wheat fields. Table 5 is a potentially practical application based on the prior assumption. The table presents a total classification of 87%, with almost no mistakes (98%) in the no spray category, and more than 80% accuracy for GW or BLW herbicide application. The threshold for weed control is influenced from biological and economical factors, and therefore is not constant. If a threshold for detection of more than 5% FC weed is adequate, then maybe this algorithm can be applicable.

Table 2. Classification matrix of pure leaf spectra by category, full spectral range

Observed \ Predicted	Percent correct	Wheat	Chickpea	BLW	GW
Wheat	**100**	**32**	0	0	0
Chickpea	**100**	0	**28**	0	0
BLW	**100**	0	0	**174**	0
GW	**99**	1	0	0	**66**
Total	**99.7**	33	28	174	66

Table 3. Canopy classification matrix, full spectral range, homogeneous samples (all)

Observed \ Predicted	Percent correct	Wheat	BLW	GW	Soil
Wheat	**90**	**46**	1	2	2
BLW	**71**	4	**17**	3	0
GW	**69**	4	1	**20**	4
Soil	**100**	0	0	0	**24**
Total	**84**	54	19	25	30

Table 4. Canopy classification matrix, 11 narrow bands, homogeneous samples (more than 30% vegetation coverage)

Observed \ Predicted	Percent correct	Wheat	BLW	GW	Soil
Wheat	**97**	**36**	0	0	1
BLW	**92**	0	**24**	2	0
GW	**96**	1	0	**22**	0
Soil	**95**	1	0	0	**20**
Total	**95**	38	24	24	21

Table 5. Herbicide application classification matrix

Observed \ Predicted	Percent correct	No spray	BLW herbicide	GW herbicide
No spray	**98**	**52**	1	0
BLW herbicide	**82**	9	**46**	1
GW herbicide	**81**	5	1	**26**
Total	**87**	66	48	27

In order to examine the ability to quantify the fractional vegetation cover prediction from homogeneous canopy spectra PLSR was applied. The PLSR was applied for each category separately and for all the categories together (Table 6). When all the categories were together, which simulates situation that they are unknown, the PLSR function had to classify and to give quantitative value. When the PLSR performed separately for each category the R^2 and RMSEP values were better than the all categories combination.

As expected, in case of all the categories together when predicting total vegetation the results are much better. This ability to predict vegetation in general better than the three categories (crop, GW, and BLW) could be due to an incorrect classification of the spectra category by the PLSR function. The results in general show that in order to develop practical application there is a need to explore the abilities farther, not only by ASD spectrometer that averages certain area to one spectrum but also by images with high spatial and spectral resolutions as can be obtained by the Spectral Camera HS.

The hyperspectral image (Fig. 2) presents the same image as presented in Figure 1 with the frame. The image (Fig. 2) is already in relative reflectance values and limited to the delimited frame area only. The time 10 zoom window of the ENVI software can be used to examine the spatial resolution, pixel size is around 0.05 mm. The relative reflectance spectra of soil, wheat, GW, and BLW obtained from the image presented in Fig. 2 are shown (Fig. 3). The soil spectra is completely different and easy to distinguish. In addition, wheat, GW, and BLW spectra show differences that are potential base for spectrally separating the three groups in order to allow spatial identification. When observing the BLW spectrum the NIR reflectance is relatively high (as expected according to the literature). The wheat and GW have almost the same signature in the NIR region but they behave differently in the red – green area. Therefore, similarly to the ASD's spectra, potentially crop, GW, and BLW can be separated by applying GDA as well as classification methods for continuous spectra. They also might be separated by some narrow bands as well as wider VENμS bands, or by known vegetation indices e.g., the Green Normalized Difference Vegetation Index (GNDVI) (Gitelson and Merzlyak, 1998) and the Red-Edge Inflection Point (REIP) (Guyot and Baret, 1988).

Table 6. Fractional vegetation covers prediction for wheat fields (R^2 values)

	N validation	Crop	GW	BLW	Total vegetation
Wheat and soil	76	0.86			
GW and soil	53		0.90		
BLW and soil	45			0.90	
Wheat, GW, BLW, and soil, unclassified	174	0.52	0.61	0.72	0.86

Fig. 2. Spectral Camera HS image

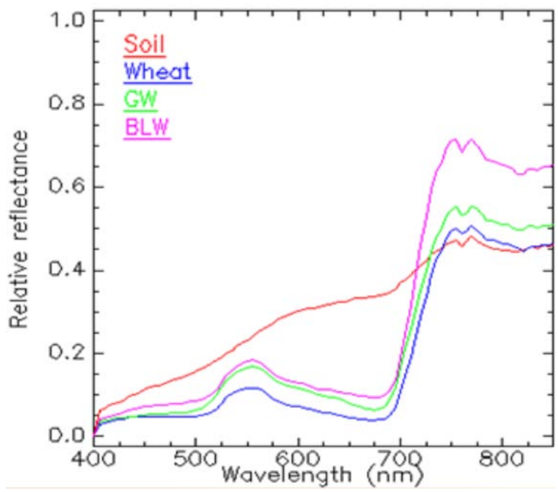

Fig. 3. Relative reflectance spectra

SUMMARY AND CONCLUSIONS

Weeds management demands high financial expense and has an environmental affect. In order to maximize the economical profit and minimize the environmental affect this work aims to find methods for crop and weeds classification. Methods that will allow site specific weed management in order to enable the application of the suitable herbicide only in the place and time needed. Results show abilities to separate crop from weeds as well as potential herbicide practical application. It was concluded that spectral separation between crop and weeds, GW as well as BLW is possible in general and in more details:

- The spectral characteristics of the pure leaf spectra enable precise classification of the different plant categories and genera.

- Classification of crop, GW and BLW by canopy reflectance gives highly accurate results when homogeneous spectra are measured. For heterogeneous spectra herbicide usage was proved to be potentially applicable.
- Several bands including red-edge bands can classify crop and weeds as good as the entire spectra (400 – 2400 nm) and therefore can be potentially implemented for crop and weeds classification.

In order to create applicable system there is a need to explore the mixed pixel issue, the Spectral Camera HS will be tested for this purpose.

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