Classification of sugar beet and volunteer potato reflection spectra using a neural network to select discriminative wavelengths

A.T. Nieuwenhuizen[1], J.W. Hofstee[1], J.C. van de Zande[2], J. Meuleman[2], E.J. van Henten[1,3]

[1]Farm Technology Group, Wageningen University, P.O. Box 17, 6700 AA Wageningen, The Netherlands, Email ard.nieuwenhuizen@wur.nl

[2]Field Technology Innovations, WUR, Plant Research International, P.O. Box 616, 6700 AP Wageningen, The Netherlands

[3]Wageningen UR Greenhouse Horticulture, P.O. Box 644, 6700 AP Wageningen, The Netherlands

Abstract

Volunteer potato plants are important weeds in sugar beet crops in the Netherlands. As a consequence, much attention is paid to the control of these weeds. The objectives of this study are to determine the reflectance properties of volunteer potato and sugar beet and to compare the ability to separate sugar beet and volunteer potato at different growth stages, using spectral reflectance characteristics. Multispectral recordings of five sugar beet and five volunteer potato plants were taken in 2006 and 2007 at three different growth stages. The recordings contained vegetation reflection in 167 wavelength bands between 450 and 1665 nanometer. A neural network approach was successfully used to identify sets of 10 discriminating wavelength bands both for the range of 450-900 nm as well as in 900-1650 nm bands. Sets of wavelengths did not uniquely discriminate between sugar beet and volunteer potato plants on measurement day and soil type. Therefore a sensor system that combines and adaptively uses the reflectance properties of the wavelengths between 450 and 1650 nm is needed for detection of volunteer potato plants between sugar beets.

Keywords: weed, detection, discriminant analysis, sensors, analysis, intelligence

Introduction

One of the important weeds in sugar beet crops in the Netherlands are volunteer potato plants. As a consequence, much attention is paid to the control of these weeds. Plants sprouting from overwintered tubers are difficult to control in sugar beet, since no selective herbicides are available. Left uncontrolled, volunteer potato harbours diseases like late blight, insects, and nematode pests of potato. As a result, the positive effects of crop rotation are lost (Boydston, 2001).

Sugar beet is a common rotational crop with potato in the Netherlands. The sugar beet crop grows in rows which gives farmers better opportunities to control the volunteer potatoes with glyphosate. The space between the rows is treated mechanically or with band sprayers while the volunteer potato plants growing within the rows have to be treated manually. This task is labour intensive – up to 30 hours per ha – (Paauw & Molendijk, 2000) and automation is required to give farmers economically attractive opportunities for volunteer potato control.

The initial step in automation of volunteer potato removal is their detection. The present study designed consistent methods for volunteer potato detection within the sugar beet crop rows using the expected differences in reflective properties of the crops and the volunteer potato weed. Commercially available systems e.g. WeedSeeker (Ntech Industries Inc., Ukiah, CA, USA) distinguish green plant material from the soil and other background elements and spray only where plant material is present. However, in addition to the discrimination of green plant material and background, inter-species discrimination is necessary for volunteer potato control within a sugar beet crop. Previous researchers have used visible light image processing to discriminate between species. After soil background subtraction, plant objects were classified based on shape, colour and texture (Guyer *et al.*, 1986; Woebbecke *et al.*, 1995; Gerhards & Christensen, 2003). They were focussed on a more complex problem of discriminating between all the weed species and the crop plants. Nevertheless, this classification process still has several problems that require a solution. For example, the changing light conditions strongly influence the classification success. Occluding and twisting leaves also negatively affect the consistency of shape, colour, and texture parameters. Multispectral analysis of crop and weed reflections, to some extent, already deal with some restrictions of image processing, such as occluded leaves and inconsistent shape features (Vrindts *et al.*, 2002). In addition, multispectral measurements give information outside the visible spectrum that traditional digital cameras measure. For example, Thenkabail *et al.* (2000) took multispectral measurements from several crop species in different growth stages. However, sugar beets, our crop species of interest, were not measured. Thenkabail *et al.* (2000) indicated that narrow band ranges are suitable for discrimination between crops. Nevertheless, the influences of changing crop growth stage conditions in the field are rarely taken into account when taking experiments for crop/weed identification systems.

The objectives of this study are to determine the reflectance properties of volunteer potato and sugar beet and to assess the ability to separate sugar beet and volunteer potato at different growth stages, using spectral reflectance characteristics. The scope of the research covers spectra gathered in two different fields with two different soils, different crop varieties, and different growth stages. The spectra were gathered in 2006 and 2007. The influences of different fields and crops on characteristic wavelength reflection were investigated with neural network wavelength selection methods. The results of this research will be used to improve the detection system for a precise volunteer potato removal system.

Material and methods

Multispectral recordings of five sugar beet and five volunteer potato plants were taken in 2006 and 2007. The identical plants were recorded at three different growth stages. The recordings contained vegetation reflection at 167 wavelength bands between 450 and 1665 nm. A minimum of 100 spectra were recorded for each plant that was measured. One spectrum measurement is the reflection of 1 mm^2 vegetation.

In-field data recording

On May 17, June 2, and June 20, 2006, spectral measurements were taken on two fields in Wageningen, The Netherlands. On May 15, May 29, June 12, and June 19, 2007, again measurements were taken on two fields in Wageningen, The Netherlands. The first field had a clay soil and the second field had a sand soil. In both fields, sugar beet and volunteer potato were present. Due to crop rotation, the identical fields as used in 2006 could not be used in 2007, but they were within a range of 500 m of each other and of the same type of soil. The number of plants measured is given in Table 1. At some dates data was not recorded due to growth stage or missing plants as a result of weed control practices on the farm.

Figure 1 ImspectorMobile measurements in sugar beet field. A and B are reflectance references in the field of view of sensor 1 and sensor 2 respectively. C are plastic sheets covering vegetation that was not recorded. D is one of the plants recorded by sensor 1.

The ImspectorMobile (Molema *et al.*, 2003) vehicle was used to take measurements of sugar beet plants and volunteer potato plants in each field (Figure 1). The plants were randomly chosen in the field and marked for the successive measurement days. To be sure that only sugar beet or volunteer potato reflections were measured, the area before and after the plant was covered with blue plastic sheets, measurements on the blue sheets were neglected in the analysis (Figure 1). Xenon flash lights and adequate shielding to prevent sunlight influence were used to maintain constant lighting conditions. Furthermore, a Spectralon® (Labsphere, North Sutton, NH, USA) 50% reflectance reference panel was measured in each recording to standardise the measured reflectance. Depending on the actual growth stage, between 20 and 30 line spectra were recorded from each plant. Recordings from 450 to 900 nm were done with sensor 1 that consisted of a V9 Imspector (Specim, Oulu, Finland) and a Kappa camera and recordings from 900 to 1650 nm were done with sensor 2 that consisted of a N17 Imspector (Specim, Oulu, Finland) and an Indigo camera. A slit of 80 micron was used within both spectrographs. Due to the slit width, sensor 1 and sensor 2 produced 91 and 75 wavelength bands of 5 nm and 10 nm bandwidth respectively. Both sensors had a field of view of 1.2 mm by 12 cm and the height above the ground was 50 cm. The driving velocity was approximately 1 cm s^{-1}. The precise measurements and the amount of lines recorded resulted in up to 2×10^5 spectra each measurement day. Therefore, the data was reduced to prevent correlation of the spatial neighbouring data points. The spatial resolution was reduced to five mm blocks perpendicular to the driving direction. The data from sensor 1 and sensor 2 were separately analysed as they were measured independently in the field (see Figure 1). After data reduction, soil spectra were removed from the dataset based on the following equations for sensor 1 and sensor 2.

$$\text{Pixel is plant if}: \frac{R_{680}}{R_{743}} < 0.5 \text{ and } \frac{R_{555}}{R_{680}} > 1.0 \text{ and } R_{680} < 0.15 \text{ and } NDVI \geq 330 \qquad (1)$$

Where R_{743} is the interpolated reflectance between R_{740} and R_{745}. The NDVI is defined as

$$NDVI = 1024 \times \frac{R_{750} - R_{675}}{R_{750} + R_{675}} \qquad (2)$$

$$\text{Pixel is plant if}: \frac{R_{1456}}{R_{1130}} < 0.7 \text{ and } R_{1456} < 0.3 \quad (3)$$

Where R_{1456} is the interpolated reflectance between R_{1450} and R_{1460}. These equations are developed and described in detail by Schut *et al.* (2003)

Table 1: Overview of measurements in 2006 and 2007. The recording dates and soil types, the number of sugar beet and potato plants recorded, and the number of spectra recorded for both sensors are shown. Measurements on clay soil were delayed in 2007, due to a later emerged crop in the fields.

					Sensor 1		Sensor 2	
Analysis #	Recording date	Soil type	Sugar beet plants	Potato plants	Sugar beet spectra	Potato plant spectra	Sugar beet spectra	Potato plant spectra
1	17-5-2006	clay	5	5	179	779	228	1510
2		sand	5	5	426	1690	1003	569
3		clay+sand	10	10	605	2469	1231	2079
4	2-6-2006	clay	5	3	744	263	2213	971
5		sand	5	4	4260	115	4720	265
6		clay+sand	10	7	5004	372	6933	1236
7	20-6-2006	clay	5	4	4922	4922	4268	4267
8	15-5-2007	sand	5	5	343	1475	91	218
9	29-5-2007	clay	5	5	960	6795	599	1433
10		sand	5	5	1859	5938	390	2130
11		clay+sand	10	10	2819	12732	989	3563
12	12-6-2007	clay	5	5	546	1376	3208	1151
13		sand	5	5	0	414	1454	198
14		clay+sand	10	10	546	1790	4662	1349
15	19-6-2007	clay	5	5	932	3112	6374	5830

The sugar beet and potato plants recorded on clay, on sand soil, and the soils combined were used to do 15 discriminant analyses, as shown in Table 1. The resulting spectra were identified as sugar beet and volunteer potato spectra using a variable selection method followed by a classification. A variable selection method was chosen as for future detection systems specific discriminating wavelengths need to be identified. To overcome the restrictions of only investigating linear relationships with linear discriminant analysis as variable selection method, a neural network wavelength selection method was used. A fully connected Kohonen neural network with three layers was trained and used for classification. The input layer consisted of the reflection variables, the hidden layer consisted of one, two or three hidden neurons, and the output layer consisted of two neurons, one for the volunteer potato class and one for the sugar beet class.

The wavelength selection and classification procedure was as follows: fifty percent of the dataset was used for training the neural network and fifty percent was used for verification of the classification. A forward inclusion method of input variables was used. More specifically, the first variable separates the two output classes the best with a net including one input variable. Each next step the net is expanded with one input variable that separates the two output classes better compared to the remaining wavelength bands and increases classification accuracy. The inclusion of variables was stopped when no increase in correctly classified spectra was seen.

After the selection and classification procedure, a sensitivity analysis was done. The selected wavelength bands were inserted into the neural network at once and a leave-one-out classification was performed. With this method the discriminative power of 10 wavelengths within the set of selected wavelengths could be determined. To summarize the results of the 15 analyses, the soil types and the measurement days the following equation was used:

$$\text{Normalized discriminative power (w)} = \frac{\sum_1^N \text{rank}_w}{\text{Total rank points}} \tag{4}$$

where N is the total number of 15 analyses, rank_w is the rank of the wavelength band in the leave-one-out classification. The highest ranking wavelength band received 10 points, the lowest ranking wavelength band received 1 point. The sum of the rank points was divided by the total rank points given for the 15 analyses which yields the normalized discriminative power of the wavelength band w as a result. The classification accuracy was determined as the quotient of correctly classified spectra and total spectra in the analysis. The classification accuracy was used to evaluate the results of discrimination with 1, 2, and 3 hidden neurons, and to evaluate the results of discrimination between sand soils, clay soils and sand and clay soils combined.

Results

The forward inclusion approach for selecting discriminative wavelengths reduced the number of wavelengths needed for classification. The reduction was from 167 to a maximum of 10 wavelength bands needed for > 90% correct classification of the spectra. This was valid for the simpler neural networks with one or two hidden neurons in the net, as well as for the more complex neural network with 3 hidden neurons in the hidden layer.

The mean classification accuracy was 97.67 %, 98.85 %, and 99.03 % for 1, 2, and 3 hidden neurons respectively for sensor 1 and the classification accuracy was 96.46 %, 97.96 %, and 98.49 % for 1, 2, and 3 hidden neurons respectively for sensor 2. This shows that more complex networks better model the reflectance response of the crops to distinguish between them. This holds for both sensor 1 and 2. Additionally, sensor 1 better modelled the reflectance properties compared to sensor 2.

The spectra recorded on the sand soils were better discriminated than the spectra recorded on the clay soils. This resulted in a higher correct classification accuracy of 98.8 and 98.2% compared to 96.5 and 94.7% for both sensors 1 and 2 respectively, when a network with 1 hidden neuron was used. The networks with 2 and 3 hidden neurons showed a higher classification accuracy for sand soils as well.

In 13 out of 15 analyses a combined set of 10 wavelengths was needed to reach a classification accuracy over 95%. These sets of wavelengths were different between the analyses. In two cases less variables were needed to achieve a classification accuracy larger than 95%. In one case on the sand soil at 17-5-2006 only two bands, 855 and 715 nm, were needed. In another case on the clay soil at 29-5-2007 only one band, 1490 nm, was needed.

Depending on the complexity of the neural network, different wavelengths scored higher on their normalized discriminative power. This can be seen in Table 2 where for example band 765 nm was selected and scored high in a simple net with 1 hidden neuron. However, this band was not within the most important bands in a net with 2 and 3 hidden neurons.

Table 2: Normalized discriminative power of the ten highest ranking wavelength bands for the analyses for 1, 2, and 3 hidden neurons in the neural network. The upper half of table covers results for sensor 1, the lower half of the table covers the results for sensor 2. The numbers shown are for the two soils together, and for the measurement days together.

1 hidden neuron		2 hidden neurons		3 hidden neurons	
wavelength band	normalized discriminative power	wavelength band	normalized discriminative power	wavelength band	normalized discriminative power
765	5.4	855	4.2	450	5.6
515	5.0	770	3.9	855	5.5
470	4.1	550	3.3	525	5.1
900	3.9	690	3.2	745	4.0
510	3.4	705	3.2	515	3.5
525	3.4	535	3.1	590	3.3
855	3.2	730	3.1	895	3.2
780	3.0	780	2.7	690	2.8
715	2.9	890	2.7	735	2.8
825	2.7	525	2.5	825	2.5
1440	6.0	1530	8.0	1530	10.5
1530	5.8	1470	5.5	1470	5.1
900	4.7	1120	5.0	1320	4.2
1430	4.7	1590	4.5	1280	3.5
1370	4.0	1380	4.2	1360	3.9
1650	4.0	1280	3.2	1490	2.8
1510	3.4	1490	3.2	1410	2.7
1380	3.2	910	3.0	1440	2.5
1590	3.2	1450	3.0	1520	2.4
910	3.0	1430	2.9	1030	2.3

Figure 2 shows the discriminative power of the wavelength bands of the two sensors, after the sensitivity analyses were applied. The graph shows all the wavelength bands that were selected and one can see that the selected bands are quite evenly distributed over the available wavelengths. So, bands from both the visible as well as from the near-infrared region were needed for discrimination. The largest bubble represents band 1530 nm that was – always in combination with other bands – one of the most powerful discriminative bands.

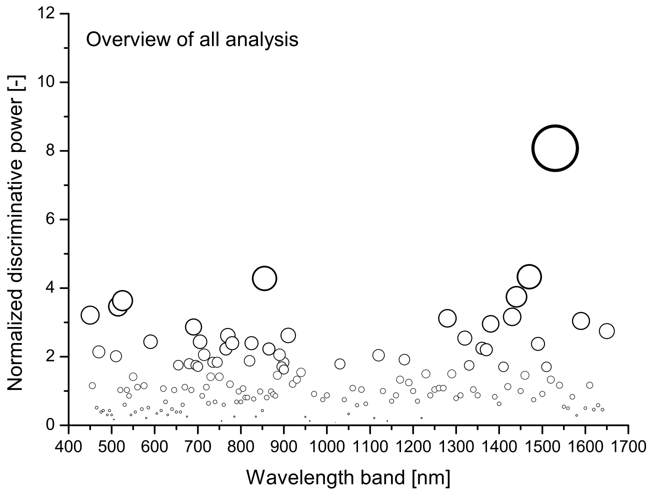

Figure 2 The normalized discriminative power between sugar beet and potato reflectance spectra of a specific band is shown as a function of all measured wavelength bands. Larger bubbles indicate larger discriminative power. The figure shows a combined summary for the 15 analyses of neural networks with 1, 2, and 3 hidden neurons.

Discussion

The spectra from the two sensors could not be linked against each other as the places on the plants were not recorded at the same time, as can be seen from the figure of the ImspectorMobile (Figure 1). This hindered combinations of wavelengths of both sensors to be selected as discriminative. Probably combinations of wavelength bands of both sensors could have had more discriminative power. The classification accuracies were higher for sensor 1. This indicates that the wavelength bands between 450 and 900 nm have a higher information content compared to the wavelength bands between 900 and 1650 nm, as the neural network was configured identical for training and classification.

In all analyses –except two– combinations of 10 wavelengths were needed to discriminate between the reflectance spectra of the two crops. These combinations of bands were different between the fields and between the days of measurement, therefore the discriminating wavelengths could not be generalized onto the 15 analyses. Our results show that the spectral reflectance properties of growing plants change in time and are different for soil types. This hampers the selection of unique bands suitable for discrimination between the crop species.

This research as well as the research by Vrindts *et al.* (2002) selected discriminative wavebands between crops and weeds. Their selection methods were statistical linear discriminant analyses that could not represent nonlinear relations like neural networks in this research. In the research of Vrindts *et al.* (2002) the crops and weeds were measured on specific growth stages and changing light conditions, which did not result in specific wavelengths for crop-weed detection, applicable in changing conditions.

From the bands that were selected, 1530 nm was one with a relatively high discriminative power within the sets of 10 bands. The 1530 nm band relates to the starch content of the plants as described by Curran (1989). This band ranked high, although it was in all cases supported by other wavelengths to be discriminative.

Conclusion

Both in the visual and in the near-infrared reflection region, combinations of wavelengths were responsible for discrimination between sugar beet and volunteer potato plants. A neural network approach was successfully used to identify sets of 10 discriminating wavelength bands both for the range of 450-900 nm and 900-1650 nm. These sets of wavelengths were not unique for discrimination on measurement day and soil type, therefore a sensor system that combines and adaptively uses the reflectance properties of the wavelengths in the bands between 450 and 1650 nm is needed for detection of volunteer potato plants between sugar beets.

Acknowledgements

The authors would like to thank Unifarm Wageningen for providing the experimental fields and Willem de Visser for their assistance with the experiments. This research is supported by the Dutch Technology Foundation STW, applied science division of NWO and the Technology Program of the Ministry of Economic Affairs. Secondly the Dutch Ministry of Agriculture, Nature and Food Quality supported this research. The research is part of research programme LNV-427: "Reduction disease pressure *Phytophthora infestans*".

References

Boydston, R. A. 2001. Volunteer potato (Solanum tuberosum) control with herbicides and cultivation in field corn (Zea mays). Weed Technology **15**(3), 461-466.

Curran, P. J. 1989. Remote sensing of foliar chemistry. Remote Sensing of Environment **30**, 271-278.

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

Guyer, D. E., Miles, G. E., Schreiber, M. M., Mitchell, O. R., Vanderbilt, V. C. 1986. Machine vision and image processing for plant identification. Transactions of the ASAE American Society of Agricultural Engineers **29**(6), 1500-1507.

Molema, G. J., Meuleman, J., Kornet, J. G., Schut, A. G. T., Ketelaars, J. J. M. H. 2003. A mobile imaging spectroscopy system as tool for crop characterization in agriculture. In: Precision Agriculture, edited by A. Werner and A. Jarfe, Wageningen Academic, pp 499-500.

Paauw, J. G. M., Molendijk, L. P. G. 2000. Aardappelopslag in wintertarwe vermeerdert aardappelcystenaaltjes. Praktijkonderzoek Akkerbouw Vollegrondsgroenteteelt bulletin Akkerbouw, pp. 4.

Schut, A. G. T., Ketelaars, J. J. M. H. 2003. Monitoring grass swards using imaging spectroscopy. Grass and Forage Science **58**, 276-286.

Thenkabail, S., Smith, R. B., Pauw, E. d. 2000. Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. Remote sensing environment **71**, 158-182.

Vrindts, E., De Baerdemaeker, J., Ramon, H. 2002. Weed detection using canopy reflection. Precision Agriculture **2002**(3), 63-80.

Woebbecke, D. M., Meyer, G. E., Bargen, K. v., Mortensen, D. A. 1995. Color indices for weed identification under various soil, residue, and lighting conditions. Transactions of the ASAE **38**(1), 259-269.