Published in: Computers & Electronics in Agriculture (2008), vol. 62, iss. 2, pp. 141-148.
Status: Postprint (Author's version)

Selection of the most efficient wavelength bands for discriminating weeds from crop

A. Piron, V. Leemans, O. Kleynen, F. Lebeau, M.-F. Destain

Gembloux Agricultural University, Unité de Mécanique et Construction, 2 Passage des Déportés, 5030 Gembloux, Belgium

Abstract

The aim of this study was to select the best combination of filters for detecting various weed species located within carrot rows. In-field images were taken under artificial lighting with a multispectral device consisting of a black and white camera coupled with a rotating wheel holding 22 interference filters in the VIS-NIR domain. Measurements were performed over a period of 19 days, starting 1 week after crop emergence (early weeding can increase yields) and seven different weeds species were considered. The selection of the best filter combination was based on a quadratic discriminant analysis. The best combination of filters included three interference filters, respectively centred on 450, 550 and 700 nm. With this combination, the overall classification accuracy (CA) was 72%. When using only two filters, a slight degradation of the CA was noticed. When the classification results were reported on field images, a systematic misclassification of carrot cotyledons appears. Better results were obtained with a more advanced growth stage.

Keywords : Multispectral imaging ; wavelength selection ; weeds ; crop

1. Introduction

Weed management for organic carrot production poses particular difficulties. Indeed, some common annual weeds have their peak of germination around the same time as crop sowing and affect the crop growth (Turner and Davies, 2005). It has been shown that there is a significant effect of weed removal timing on the yield of carrots: the 3-week and the 5-week weeded plots have a significantly greater yield than the 7-week treatment (Turner and Grundy, 2002). To destroy these weeds, mechanical weeding is carried out between the rows, while manual weeding is realized within the rows. This second operation remains fastidious and time- and cost-consuming. It would therefore be useful to develop equipment able to destroy selectively the weeds located within the rows. This implies in a first stage the recognition of weeds from plants.

Machine vision is successfully used to recognize weeds from soil with the goal of eliminating weeds between the rows or between widely spaced individual crop plants (Perez et al., 2000; Tillett et al., 2001; Onyango and Marchant, 2003), but it is still a difficult task to recognize weeds within the rows, particularly in the case of carrots. Indeed carrots are densely sown, they do not follow a regular sowing pattern and present high variability in size and shape due to different development stages. Furthermore, some weeds are very similar to plants regarding their shape or colour and plants and weeds are often overlapping (Fig. 1). Hemming and Rath (2001) and Aitkenhead et al. (2003) reported studies involving detection of weeds among carrot seedlings. In our case however the density of the sown carrots was estimated to be five to ten times higher, which makes the separation of individual plants or leaves more complicated.

Fig. 1 *- Picture of a typical carrot line (horizontally, in the upper part of the image) with weed infestation at an early growth stage.*

Within the scope of recognizing weeds from crops, numerous researches have been conducted to analyse the factors that influence spectral reflectance of leaves. This parameter is influenced by the interaction between the species and the growth stage (Franz et al., 1991; El-Faki et al., 2000; Zhao et al., 2005), by stresses such as water or nitrogen deficiency (Goel et al, 2003; Zhao et al., 2005), by the angle between the leaf and the camera optical axis (Franz et al., 1991; Haralson et al., 1997 cited in Noble et al., 2002) and by the substrate nature (Noble and Crowe, 2001; Noble et al., 2002).

Senescence also alters plants' spectral characteristics (Daughtry and Biehl, 1985).

Several authors investigated multispectral imaging systems to differentiate weeds from crops. Two main methods are reported in the literature: spectrophotometric and camera/filter methods, used either in laboratory conditions or in the field.

Using a spectrograph, Borregaard et al. (2000) studied beet, potatoes and various weed leaves at an early growth stage under artificial lighting. The best classification rate (89%) was obtained by using two wavelengths (694 and 970 nm) to discriminate sugar beet and weeds. For potatoes and weeds, the best classification reached 94% using 686 and 856 nm wavelengths. The method for selecting the wavelengths was not mentioned. Feyaerts and Van Gool (2001) developed a spectrograph with a low spectral resolution (35 nm) and used it in field to discriminate beets from five weed species. The wavelength selection was carried out by examining weed-crop pairs to find the wavelengths that maximized a separation function. The selected wavelengths were 441, 446, 459, 883, 924 and 988 nm with a correct classification rate of up to 83%. Wang et al. (2001) developed an optical weed detector based on phototransistors. To select appropriate wavelengths, spectrometric measurements were performed on three weed species, wheat and soil at two growth stages, under laboratory conditions. The selected wavelengths were 496, 546, 614, 676 and 752 nm, the method used is not explicitly given. Measurements on potted plants were performed under artificial lighting. The classification rate between the weeds considered as a single group and the crop reached 72% for sufficiently densely weed infested samples. For lower infestation rates, the classification rate was below 50%. Vrindts et al. (2002) compared the results from a laboratory study on leaves using a spectrometer to infield natural lighting spectrography results. Two crop plants (beet and maize) and seven weed species were studied. A 100% classification rate was obtained when using nine wavelengths to discriminate corn from weeds and using eight wavelengths to separate beets from weeds. For the spectrographic data, a stepwise discriminant approach yielded slightly lower classification rates (93% with nine spectral bands for beet and 91% using eight bands for corn). Authors found that lighting conditions strongly influenced the classification rates and the discrimination was only efficient with data taken under identical and constant lighting.

Using a camera with a filter wheel holding four filters (RGB and infra-red), Franz et al. (1991) took images of four weed species and soy leaves under controlled lighting. Using five statistical features of the leaf images, the classification rate was up to 94% with manually selected samples and taking into account the relative position of the plants and the lighting system. Zhang and Chaisattapagon (1995) selected five filters to discriminate five species of weeds from soil and wheat at two growth stages, on potted plants located under artificial lighting. The selection of those filters was done among 15 by computing the means and coefficient of variation of the grey level ratios of all possible filter pairs and selecting those that exhibited the most different means and a small coefficient of variation over a number of samples.

Each of these studies found at least one useful wavelength above 700 nm, which suggested that it was important to scan beyond the visible spectrum. Nevertheless, the selected wavelengths were highly variable, depending on the pair crop-weed to discriminate, on the methodology (measurement in laboratory controlled conditions or in the field), on the instrument used to perform the measurement (spectrograph or camera equipped with filters). The method of selecting the most appropriate wavelengths is not always clearly identified nor is it optimal.

In some cases, good classification results are obtained. They may be attributed to particular conditions, such as crop regularly spaced in the field with no overlapping (Borregaard et al., 2000; Feyaerts and Van Gool, 2001), clearly different macrostructures of weeds and crops (Franz et al., 1991) or presence of a particular colour on certain plant stems (Zhang and Chaisattapagon, 1995; El-Faki et al., 2000).

The long-term objective of this study is to develop a device able to detect individual weeds within the rows from carrots under field conditions by using computer vision techniques. This paper describes the first stage of this research: selecting the most appropriate wavelengths bands for an image acquisition device. To perform this operation, we choose to work with a camera equipped with a wheel filter and to acquire infield images under controlled lighting. The choice of a camera is based on the difficulty of taking measurement with a spectrometer on young (and therefore small) plants, especially in bracts and other small structures, which would be necessary since different parts of the same plant have different spectral characteristics (Hunt et al., 2004). It was chosen to work on living plants since senescence can alter plants' spectral characteristics as stated earlier.

2. Materials and methods

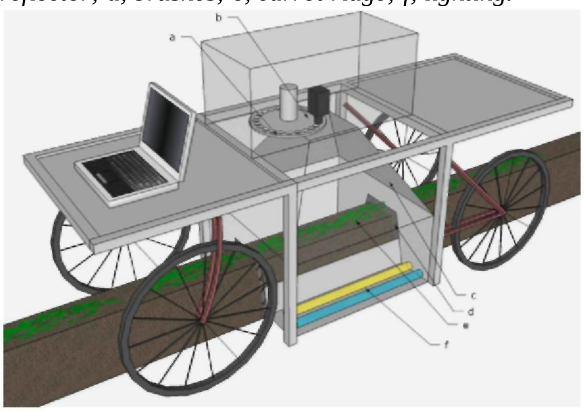
2.1. Study site description

The study concerned two carrots' varieties without distinction, *Nerac* F1 and *Namur* F1, sown on 27 April, 2006 in an experimental field in Gembloux (Belgium). The soil of this field is silty (14% clay, 78% silt, 8% sand). Approximately 200 linear metres of rows were mechanically sown at a density of 10-15 seeds per 100 mm long by 50 mm wide which is a common commercial planting density. Several species of weeds were naturally present in the field and others were manually introduced. The main species were the following at the time of data acquisition: *Sonchus asper I.*, *Chenopodium*, *Achenocloa*, *Cirsium*, *M. perennis*, *Brassica* and *Matricaria maritime*. Other species might have been present. Weeds were considered as a single class in the discrimination approach since they appear in fields in unpredictable species and quantities.

2.2. Image acquisition

The scene contained carrot rows infested by various weed species (Fig. 1). A mobile multispectral vision system was designed to acquire top-down images of this scene (approximately 200 mm × 250 mm) in the visible and the near infrared spectra. The acquisition system included a monochrome 12 bits 1.3 megapixels camera (C-Cam BCI-5) with a filter wheel equipped with 22 band pass interference filters[1] (Table 1). The filters were selected to cover the sensitivity range of the camera sensor and are relatively wide (40-100 nm FWHM) to allow potential future real-time use. The rotation of the filter wheel was controlled by a stepper motor. An artificial lighting system was used to avoid any interference with natural lighting. The lighting system used a combination of fluorescent and incandescent light sources covering the whole imaged spectrum and giving an indirect diffuse light. This combination ensures a light intensity sufficient to keep exposure times reasonable in all wavebands of interest. The system was designed to occlude natural light by physically shielding the target from external light, as completely as possible. The occlusion was tested by confirming that when taking images in all spectral bands on a sunny day without the artificial lighting system, the exposure times required to get an image were well beyond the capacity of the sensor to acquire images. Prior to each acquisition, the lighting system was powered for about 15 min to get a stable lighting. The vision system is presented in Fig. 2. Exposure times for each spectral band were determined before data acquisition on potted plants' leaves since the amount of light, the filter transmission and the camera sensitivity vary in each band. The mean grey level of the leaves was computed and the shutter speed modified until the mean grey level reached approximately 50%. For two of the 22 filters (500-40 and 650-40), the exposure times were longer than one second and thermal noise was readily apparent in the images. To solve that problem, dark frame subtraction noise reduction followed by a 3 × 3 median filtering to remove remaining noise was applied.

Fig. 2 *- Schematic view of the acquisition device. Legend: a, filter wheel and stepper motor; b, camera; c, reflector; d, brushes; e, carrot ridge; f, lighting.*



Images were acquired at an early growth stage of both carrots and weeds (from 1 week after crop emergence to 19 days later, see Table 2) which is the usual period for manual weeds removal. Indeed, early weed detection can increase yields and weed elimination becomes increasingly difficult with plant growth. In May, the soil was wet and dark, while it was dry and lighter in June. A total of 51 multispectral images were acquired at random locations in the parcel. The number of images acquired per day varied according to meteorological conditions: strong winds made the acquisition of images difficult because of the movement of plants and/or camera.

[1] Filters are referred to in this document under the following format: *a-b*, where *a* is the centre in nm and *b* is the FWHM (full width at half maximum) in nm.

Published in: Computers & Electronics in Agriculture (2008), vol. 62, iss. 2, pp. 141-148.
Status: Postprint (Author's version)

***Table 1** - Filters used in the multispectral device*

Centre (nm)	FWHM (nm)
450	50
450	80
500	40
500	80
550	50
550	80
600	50
600	80
650	40
650	80
700	50
700	80
750	40
750	80
800	50
800	100
850	40
850	100
900	40
900	100
950	40
950	100

***Table 2** - Summary of acquired data (columns 5 and 6 result from the data extraction process described in Section 2.3)*

Date of data acquisition	Days after crop emergence	Soil surface state	Acquired multispectral images	Carrot seedlings pixels	Weed seedlings pixels
22 May 2006	7	Wet	10	18,828	51,664
29 May 2006	14	Wet	7	41,059	72,925
31 May 2006	16	Wet	17	69,975	135,097
7 May 2006	23	Dry	11	385,835	85,362
9 May 2006	25	Dry	6	220,771	130,255

2.3. Data pre-processing

A preliminary step of the data analysis was to extract plant (crop and weed) pixels from the multispectral images and discard the background (soil and parts of the lighting system that remain visible in the images). To achieve this goal, four multispectral images (two on dry soil and two on wet soil) randomly taken from the 51 acquired were manually segmented into two classes (plant and background) by creating masks in a computer drawing program. The pixels of each class were used as a training dataset for filter selection on basis of a quadratic discriminant analysis (QDA). It was decided to use two spectral bands on basis of earlier work (Alchanatis et al., 2005). The selection process is otherwise identical to the one described in Section 2.4 hereafter. The two selected bands were 550-80 and 750-80.

2.4. Filter combinations selection

The spectral data resulting from the pre-processing steps were analyzed using the classification method based on Kleynen's work (2003). Its general principle is to evaluate the capacity of all possible combinations of a reduced number of filters to discriminate between different objects. This method is guaranteed to return the best filter combinations which is not the case with others methods such as stepwise analysis (Dagnelie, 2006). This combination selection is computationally achievable, since the number of filters to select is small (2, 3 or 4) and the wavebands are chosen among a limited number of available commercial filters (22).

The method classifies the data either into weed or crop using a classical quadratic discriminant analysis approach (Michie et al., 1994). This method was chosen instead of neural networks (NN) since the classification rules are not dependant on the training such as for NN and it is supposedly better at extrapolation (Michie et al., 1994).

The choice of a quadratic instead of linear discriminant analysis is justified because the latter supposes the equality of covariance matrices which was unlikely because the weed classes included several species.

Classification accuracy (CA) represents the pixels correctly classified either as carrots or weeds, expressed as a percentage of the true carrots or weeds pixels. Overall classification accuracy was the mean value of both CA. Overall CA was the criteria to assess the filter combination efficiency.

Due to the large amount of measurement points (Table 2, columns 5 and 6), three random samplings were applied to extract 10% (for each sampling) of the pixels of the carrot leaves and the same amount of weeds. Resubstitution validation was used to verify that the three data subsets gave the same results in terms of filter selection and CA. All the filter combinations selected for the discrimination between carrots and weeds were also evaluated with regards to their capacities to discriminate between soil and plants.

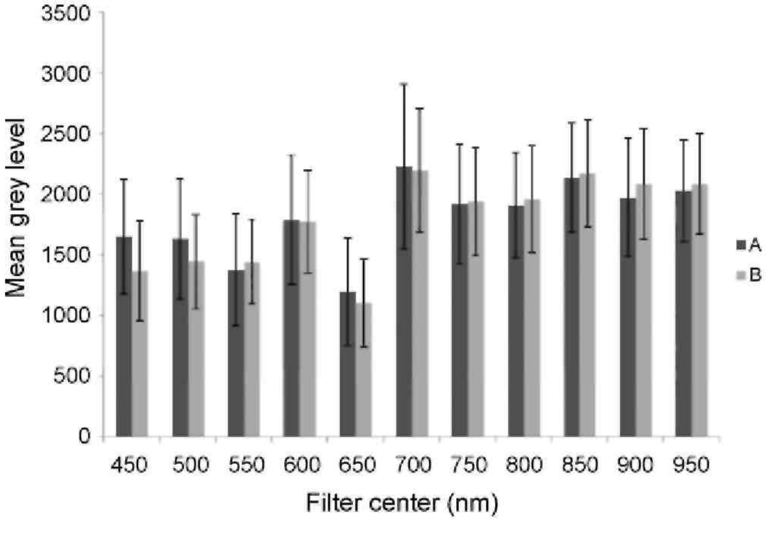
3. Results and discussion

All combinations of two, three and four filters were evaluated (C_{22}^{4} = 7315 combinations for four filters, C_{22}^{3} = 1540 for three and C_{22}^{2} = 231 for two) with regard to the overall CA. All selected filter combinations ensured the discrimination of background from the plants with an accuracy of 99%. The results of the filter combinations selection are shown in Tables 3 and 4. Only the five first values were reported as the overall CA did not decrease significantly over a large number of filter combinations. The combinations of four filters were also analyzed, but the results did not exhibit classification rates higher than the three filters combinations (overall CA of 72%) and therefore were not reported.

As can be seen from Figs. 3 and 4, the mean values of carrots and weed classes are very close while variability is high. This confirms that special care has to be taken for the filter selection method.

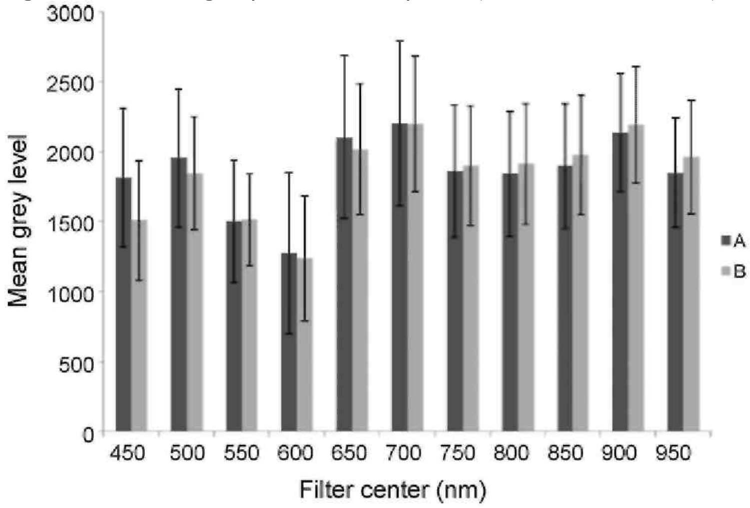
When analysing the results for combinations of three filters, and taking into account the whole dataset, the best combination of filters included three filters, respectively centred on 450, 550 and 700 nm. The overall classification accuracy was better for weeds than for carrots (except in one case): the CA of weeds was between 76 and 80%, while the CA of carrots was between 62 and 67% on the first five filters combinations. For each centre wavelength, two widths of filter were evaluated (40 or 50 nm and 80 or 100 nm). The results show that the best filter combinations nearly always use the same centres. The width of the filters does not appear to be an important factor on the classification accuracies, no overall trend can be seen among the results: the same combinations of filter centres appear with both bandwidths with similar CA when looking at the complete results. This can either mean that fine spectral details are not resolved at those widths or that those details are not significant for the classification of the species studied.

Fig. 3 *- Mean grey level of all the pixels for each class in narrow band filters (40 or 50 nm FWHM); (A) carrots, (B) weeds.*



Published in: Computers & Electronics in Agriculture (2008), vol. 62, iss. 2, pp. 141-148.
Status: Postprint (Author's version)

Fig. 4 *- Same as Fig. 3 for wide band filters (80 or 100 nm FWHM).*

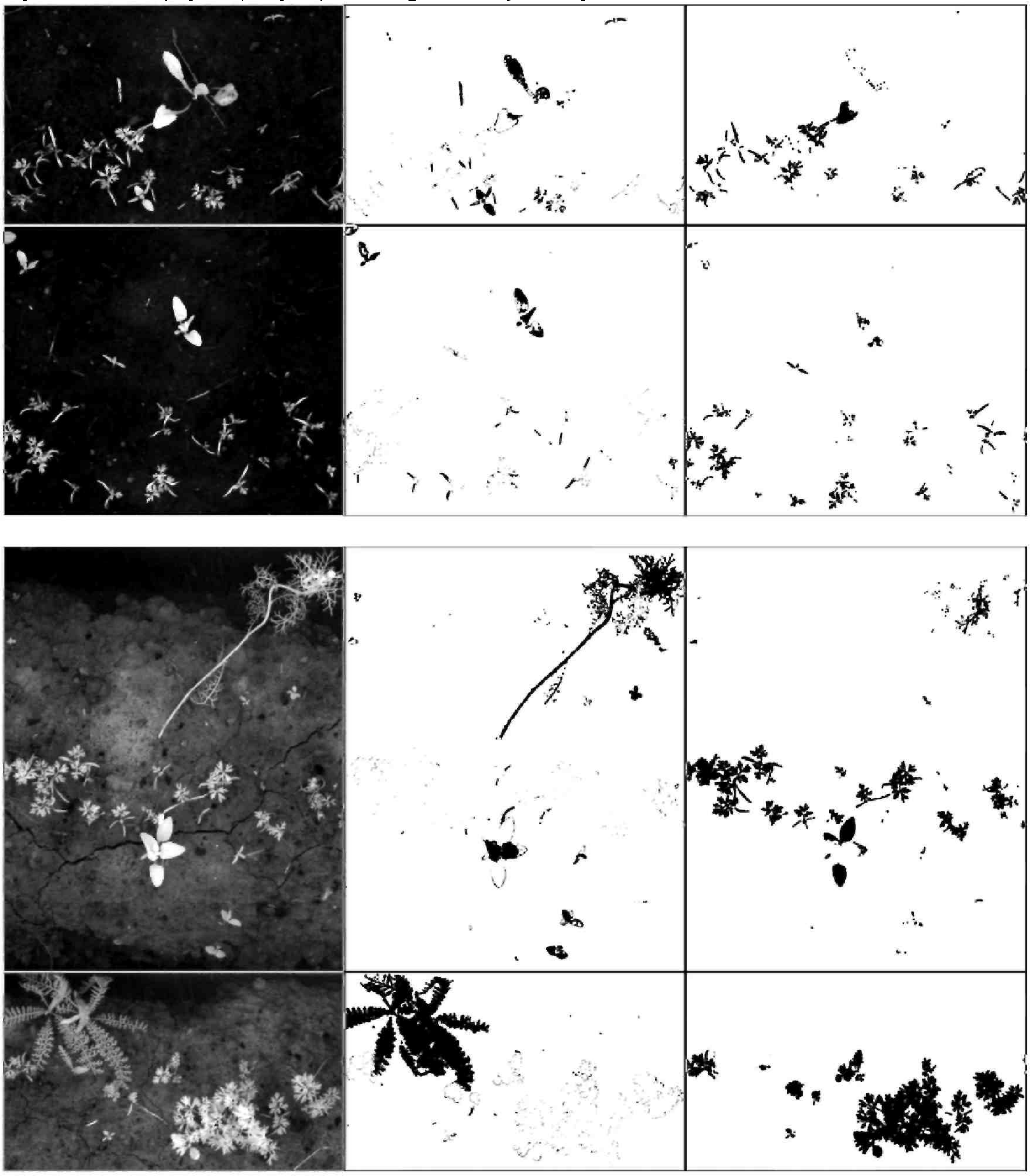


To get a better interpretation of the classification, the results were reported on the images (Fig. 5). The four examples were selected to show the classification on two soil states (wet and dry), and exhibit various weed species and growth stages. The images with the classification results overlay showed that parts of individual plants, such as pairs of opposed leaves could be misclassified. In some cases, the centre of the weeds was correctly classified while the outer regions were misclassified. This might be an effect of the variation of spectral properties with the geometry of the scene, since the angle between the leaf and the camera optical axis varies from the periphery to the centre of the weed. On the other hand, cotyledons are nearly systematically misclassified, confirming previous studies revealing different spectral characteristic between cotyledons and leaves of the same plant (Franz et al., 1991; Gee et al., 2004).

Table 3 - *Five first best combinations of three filters for the entire dataset (a), data subset corresponding to data acquired from 7 to 16 days after crop emergence (b) and acquired from 23 to 25 days after crop emergence (c), classification accuracy (CA) in %*

Filters			Overall CA	CA carrots	CA weeds
(a) 12 bits, entire dataset					
450-80	550-80	700-50	72	66	78
450-50	550-80	700-50	71	66	77
450-80	550-50	750-40	71	66	76
450-80	550-50	700-50	71	67	76
450-80	550-50	700-80	71	62	80
(b) 12 bits, data subset acquired between 7 and 16 days after crop emergence					
450-80	550-80	750-40	68	58	78
500-80	550-50	750-40	68	59	77
500-80	550-80	700-80	68	76	59
450-50	550-80	750-40	68	59	76
450-80	550-50	750-40	68	59	76
(c) 12 bits, data subset acquired between 23 and 25 days after crop emergence					
450-80	550-50	950-40	76	69	84
450-80	550-80	700-50	76	70	83
450-80	550-50	700-50	76	68	84
450-80	550-50	850-40	76	68	83
450-50	550-80	700-50	76	71	80

Fig. 5 *- Four examples of classification on images using the three selected optimal filters (reference images left, weed class outputs center, carrot class outputs right). From top to bottom, images were taken 14, 16 (wet soil) days and 23, 25 (dry soil) days after emergence, respectively.*



The impact of the misclassification of cotyledons on the classification accuracy is likely small since cotyledons have a small area compared to the rest of the carrot's leaves.

Whole plants cannot readily be identified on the those images, further research is required to perform this operation, using other computer vision techniques such as shape or texture analysis.

When analysing Table 3b and c, it appears that CA varied significantly with the growth stage. In the data acquired from 7 to 16 days after crop emergence, the overall CA was 68%, while from 23 to 25 days after crop emergence, it reached 76%. This better CA in a more advanced stage corresponded to a greater overlap and proportion of leaves over cotyledons. Since cotyledons are not correctly classified in earlier data, this lowers the overall CA. Furthermore, some interaction might occur between the growth stage and the soil. The soil became progressively drier during the carrots growth inducing a greater reflectance in the NIR part of the spectrum. On the other hand, leaf transmittance of NIR wavelengths is higher than transmittance of visible wavelengths but the differenciated evolution between the carrots and weeds leaves is unknown. Spectral characteristics of plants are also influenced by soil water content. These factors could also explain the change in CA if they intensify the difference on the perceived spectral characteristics of weeds and carrots leaves. Unfortunately, growth stage and soil moisture are strongly correlated in the dataset so their effects cannot be distinguished.

***Table 4** - Five first best combinations of two filters for the entire dataset*

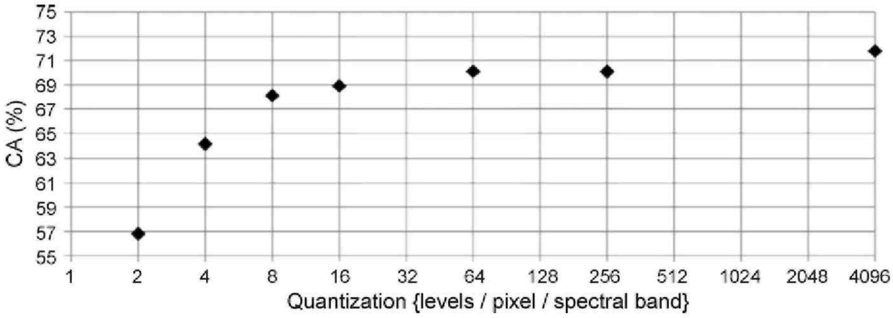
Filters		Overall CA	CA carrots	CA weeds
450-80	550-50	69	64	74
450-80	600-50	69	63	75
450-80	550-80	69	64	74
450-50	550-50	69	64	73
450-50	600-50	68	63	74

The results using only two filters (Table 4) showed a slight degradation of the CA. Notably, none of the first selected combinations of filters were located in the infrared part of the spectrum as it was the case for the three filter combinations and in literature. However, this only means that for a combination of only two filters, more information is available in the visible spectrum. Reported on images, the results are visually qualitatively indistinguishable from those obtained with three filters.

With regards to a real-time implementation of the discrimination method and a simpler acquisition system, the possibility of working with a reduced quantization for the data was assessed. Fig. 6 shows the evolution of the classification accuracy with the diminution of quantization. Down to eight levels per spectral band, results are again visually qualitatively indistinguishable when transcribed onto field images and compared to full quantization (4096 levels per spectral band).

It is also interesting to note that given the combination of three filters with the best overall CA over the whole dataset (450-80, 550-80 and 700-50) and the typical sensitivity curves of colour cameras, it is plausible to build an acquisition device out of such a camera and spectrally controlled lighting.

***Fig. 6** - Relation between classification accuracy and quantization (using an optimum three filters combination for each quantization).*



4. Conclusion

An objective method for selecting the most efficient filters combination to discriminate weeds located within carrot rows was described. The data acquisition was carried out in field conditions under artificial lighting, over a period of 19 days, starting 1 week after crop emergence. During this period, the presence of weeds has the most negative effect on yield. Seven different weed species were considered (*Sonchus asper* I., *Chenopodium*, *Achenocloa*, *Cirsium*, *M. perennis*, *Brassica* and *Matricaria maritima*). The best combination of interference filters was selected among 22 commercial filters covering a range from 450 to 950 nm. This was performed by computing the highest classification rate obtained by quadratic discriminant analysis. The best combination of filters included three filters, respectively centred on 450, 550 and 700 nm. With this combination, the overall classification accuracy (CA) 72%. Those spectral bands could be acquired by a classic colour camera combined with spectrally controlled lighting.

When using only two filters, a slight degradation of the CA was noticed. The CA was also affected by the quantization of the spectral data but remained relatively constant down to a very low number of levels per band. Both results are encouraging with regards to a simpler implementation of the vision system.

When the classification results were reported on field images, a systematic misclassification of carrot cotyledons appeared. Better results were obtained with a more advanced growth stage, but still within a 5-week post-emergence weeding period that gives greater yields.

Acknowledgements

This project is funded by the "Ministère de la Région wallonne-DGTRE", project "RECADVEN" no. EPH3310300R049F/41J81

References

Aitkenhead, M.J., Dalgetty, I.A., Mullins, C.E., McDonald, A.J., Strachan, N.J., 2003. Weed and crop discrimination using image analysis and artificial intelligence methods. Comput. Electron. Agric. 39, 157-171.

Alchanatis, V., Ridel, L., Hetzroni, A., Yaroslavsky, L., 2005. Weed detection in multi-spectral images of cotton fields. Comput. Electron. Agric. 47, 243-260.

Borregaard, T., Nielsen, H., Norgaard, L., Have, H., 2000. Crop-weed discrimination by line imaging spectroscopy. J. Agric. Eng. Res. 75, 389-400.

Dagnelie, P., Statistique théorique et appliquée 2-Inférence statistique à une et à deux dimensions. De Boeck ed., Bruxelles, 2006.

Daughtry, C.S.T., Biehl, L.L., 1985. Changes in spectral properties of detached birch leaves. Remote Sens. Environ. 17, 281-289.

El-Faki, M.S., Zhang, N., Peterson, D.E., 2000. Weed detection using color machine vision. Trans. ASAE 43 (6), 1969-1978.

Feyaerts, F., Van Gool, L., 2001. Multi-spectral vision system for weed detection. Pattern Recogn. Lett. 22, 667-674.

Franz, E., Gebhardt, M.R., Unklesbay, K., 1991. The use of local spectral properties of leaves as an aid for identifying weed seedlings in digital images. Trans. ASAE 34 (2), 682-687.

Gee, C., Bonvarlet, L., Magnin-Robert, J.B., Guillemin, J.P., 2004. Weed discrimination by reflectance measurements using neural networks. In: Douzième Colloque international sur la biologie des mauvaises herbes, Dijon, France, Paris: AFPP.

Goel, P.K., Prasher, S.O., Patel, R.M., Landry, J.A., Bonnell, R.B., Viau, A.A., 2003. Classification of hyperspectral data by decision trees and artificial neural networks to identify weed stress and nitrogen status of corn. Comput. Electron. Agric. 39, 67-93.

Hemming, J., Rath, T., 2001. Computer-vision-based weed identification under field conditions using controlled lighting. J. Agric. Eng. Res. 78 (3), 233-243.

Hunt, E., Raymond Jr., McMurtry, James III, E., Parker Williams, Amy, E., Corp, Lawrence, A., 2004. Spectral characteristics of leafy spurge (*Euphorbia esula*) leaves and flower bracts. Weed Sci. 52, 492-497.

Kleynen, O., Leemans, V., Destain, M.-F., 2003. Selection of the most efficient wavelength bands for 'Jonagold' apple sorting. Posthar. Biol. Technol. 30, 221-232.

Michie, D., Spiegelhalter, D.J., Taylor, C.C. (Eds.), 1994. Machine Learning, Neural and Statistical Classification. Ellis Horwood, Chichester, UK.

Noble, S.D., Crowe, T.G., 2001. Background Effects on Apparent Leaf Reflectance. ASAE Technical Library Paper no. 01-1177, ASAE, St. Joseph, MI, USA.

Noble, S.D., Brown, R.B., Crowe, T.G., 2002. The use of spectral properties for weed detection and identification-a review. In Canadian Society of Agricultural Engineers, Saskatoon, SK. 14-17 July 2002. CSAE Paper 02-208. CSAE/SCGR, Mansonville, QC, Canada.

Onyango, C.M., Marchant, J.A., 2003. Segmentation of row crop plants from weeds using colour and morphology. Comput. Electron. Agric. 39, 141-155.

Perez, A., Lopez, E, Benlloch, J.V., Christensen, S., 2000. Colour and shape analysis techniques for weed detection in cereal fields. Comput. Electron. Agric. 25, 197-212.

Tillett, Nick, D., Hague, T., Miles, S.J., 2001. A field assessment of a potential method for weed and crop mapping on the basis of crop planting geometry. Comput. Electron. Agric. 32, 229-246.

Turner R. J., Davies G., 2005. Weed management in organic carrots, HDRA no. 298104.

Turner, R.J., Grundy, A.C., 2002. Weed control strategies in organically grown carrots UK Organic Research 2002. In: Powell, et al. (Eds.), Proceedings of the COR Conference. Aberystwyth, pp. 229-230.

Vrindts, E., De Baerdemaeker, J., Ramon, H., 2002. Weed detection using canopy reflection. Precis. Agric. 3, 63-80.

Wang, N., Zhang, N., Dowell, F.E.Y.S., Peterson, D.E., 2001. Design of an optical weed sensor using plant spectral characteristics. Trans. ASAE 44 (2), 409-419.

Zhang, N., Chaisattapagon, C., 1995. Effective criteria for weed identification in wheat fields using machine vision. Trans. ASAE 38, 965-974.

Zhao, D.H., Li, J.L., Qi, J.G., 2005. Identification of red and NIR spectral regions and vegetative indices for discrimination of cotton nitrogen stress and growth stage. Comput. Electron. Agric. 48, 155-169.