

DESIGN OF AN OPTICAL WEED SENSOR USING PLANT SPECTRAL CHARACTERISTICS

N. Wang, N. Zhang, F. E. Dowell, Y. Sun, D. E. Peterson

ABSTRACT. *Spectral characteristics of stems and leaves of various crop and weed species were studied using a diode-array spectrometer. Five feature wavelengths were selected to form color indices as input variables to a classification model for weed detection. The feature wavelengths also served as the basis for design of an optical weed sensor. Based on experimental data, color indices insensitive to illumination variations were designed and tested on the sensor. Laboratory tests showed that the sensor identified wheat, bare soil, and weeds (several species combined) with classification rates of 100%, 100%, and 71.6%, respectively, for the training data set when the weed density was above 0.02 plants/cm². The classification rates for the validation data set were 73.8%, 100%, and 69.9%, respectively. When the density of weeds was low, as in the case of a single weed plant, more than 50% of the weeds were misclassified as soil. Misclassifications between wheat and weeds were not observed at any weed and wheat densities tested.*

Keywords. *Weed, Sensor, Optical sensor, Spectral reflectance, Precision agriculture, Measurement.*

Traditional approaches to herbicide application are based on the assumption that weeds are distributed uniformly in fields. However, most agricultural fields are spatially variable in weed infestation to a certain degree. The distribution of weeds, particularly grass weeds in cereal crops, is often “patchy,” rather than even or random. Ben and Hamm (1985) pointed out that portions of cereal crop fields are free of weeds, and weed species found in different fields of the same crop are often different. The efficiency of weed control can be improved if herbicides are applied only over the weed-infested areas. A precision weed sensor combined with selective spray has great potential to improve the efficiency.

Detecting weeds in a crop field is a challenging task. With the advances of computer technologies, machine vision has been identified as a possible solution for weed detection (Thompson et al., 1990). Image-based weed sensors discriminate weeds against soil and crops using shape, texture, or color features. El-Faki et al. (1997) developed an image-based weed-detection system using relative color indices formed by RGB gray levels. The system was less sensitive to canopy overlay, leaf orientation, camera focusing, and wind effect than systems based on plant shape

and texture features. Lee and Slaughter (1998) designed and tested a real-time, intelligent, robotic, weed-control system using machine vision. An artificial neural network was implemented to classify tomato plants and weeds. Shiraishi and Sumiya (1996) developed a machine-vision-based plant-identification system using geometric shape features. Scarr et al. (1997) reported that analyzing a small, homogeneously textured subregion within a plant image is a robust approach for identifying a particular weed species. Tang et al. (1999) developed an experimental, machine-vision-based patch sprayer to perform real-time weed density estimation and variable-rate herbicide application control, as well as high-resolution weed mapping. Burks et al. (2000) applied a color co-occurrence method (CCM) using only hue and saturation statistics to develop a weed classifier, which classified five weed species with an accuracy of 93%. Elimination of the intensity statistics greatly reduced the computation time. Feyaerts et al. (1998) designed a spectral reflectance sensor using an imaging spectrograph. The results showed that, under controlled conditions, corn and sugar beet could be classified against weeds with accuracies of 90% and 80%, respectively. Tian et al. (1999) developed an intelligent sensing and spraying system, in which a real-time machine vision system was integrated with an automatic herbicide sprayer. Using real-time image-processing algorithms, coverage density, and wavelet decomposition, the system detected weed-infested zones (0.254 m × 0.34 m) rather than individual weeds. The overall accuracy of the sprayer was 100% in bare soil zones, 75% in weed-infested zones, and 47.8% in crop plant zones. Using 0.5% weed coverage as the control zone threshold, herbicide savings of 48% could be realized.

Optical sensors using spectral characteristics of plants in the visible and near-infrared (NIR) wavebands have been studied. Shropshire et al. (1990) used an optical device to measure the ratio between reflected red and NIR lights for weed detection. Felton and McCloy (1992) developed a sensor to discriminate green plants (weeds) against a

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background of soil and dead plant materials based on visible and NIR reflectance. Commercial sensors (Detectspray™ and WeedSeeker™) based on this principle were used for weed control on bare ground, including bare soil, roadsides, irrigation ditch banks, railroad right-of-ways, paved parking lots, etc., with a detection rate of higher than 95% (Blackshaw et al., 1998). Biller (1998) used the Detectspray system for weed detection and achieved 30% to 70% reduction in herbicide use. Vrindts and Baerdemaeker (1996) studied the possibility of classifying soil, crops, and weeds using spectral responses at a limited number of wavelengths. The wavelengths were selected through a discriminant analysis on spectral data of leaves of four crops (potato, sugarbeet, corn, and chicory), soil, and weeds. Visser and Timmermans (1996) developed a unique sensor that utilized fluorescence properties to detect weeds.

The advantages of optical sensors over machine-vision systems for weed detection are their low cost, simple system configuration, and high processing speed. If a limited number of feature wavelengths can be identified, optical sensors may prove to be more practical for field implementation.

The objectives of this study were:

1. To investigate the feasibility of weed detection based on spectral characteristics of crops, weeds, and soil;
2. To select feature wavelengths that can be used to discriminate weeds against crops and soil effectively;
3. To define color indices insensitive to illumination intensity;
4. To develop an optical weed sensor; and
5. To test the weed sensor at different weed densities under laboratory conditions.

PRINCIPLES OF THE OPTICAL WEED SENSOR

Design of the optical weed sensor was based on a study of spectral-reflectance characteristics of crops, weeds, and bare soil. These characteristics were measured using a diode-array spectrometer. For each weed or crop species, spectral characteristics of stems and leaves were measured separately as two individual object classes. Soil was treated as an additional class. These object classes were combined to form five major object categories: weed stem, weed leaf, crop stem, crop leaf, and soil. Spectral data were studied to select feature wavelengths, that is, the wavelengths at which contrasts in spectral responses between major object categories became distinct. Color features were defined using spectral responses at these feature wavelengths in the form of relative color indices and were used to design an optical sensor. These color indices were also used to establish a classification model through statistical discriminant analysis (DA). The classification model was tested on the optical sensor to observe its effectiveness in detecting weeds at different densities.

SPECTRAL CHARACTERISTICS OF PLANTS AND SOIL

Spectral reflectance of 35 plant species, including five crops (corn, common sunflower, soybean, sorghum, and

wheat), 30 weed species, and bare soil, were measured using a diode-array spectrometer (DA7000, Perten Instruments, Inc., Springfield, Illinois). For each plant species, reflectance spectra of leaves and stems were collected separately at two growth stages: 3 weeks and 6 weeks from the date of planting. To provide replicate spectral data, crops and weeds were planted in three groups, with the dates of planting 2 weeks apart.

Individual leaf, stem, and soil samples were placed horizontally on a spectralon disk that was illuminated with white light generated by the spectrometer via an 8-mm diameter fiber bundle, which was positioned 13 mm from the spectralon surface and oriented 45° from vertical. A 2-mm diameter probe was oriented vertically, 18 mm from the spectralon surface, to transmit the light reflected from the sample to the spectrometer, which scanned the reflectance through the visible (400–750 nm) and NIR (750–1700 nm) wavebands at 2-nm intervals and at a rate of 30 scans per second (fig. 1). For each sample, baseline (a spectrum of the spectralon background) was collected first, and then eight spectra were collected and averaged. The entire scanning and processing procedure for a sample took less than 1 second.

The measured light-reflectance first was converted to light-absorbance (eq. 1):

$$a_i = \log \frac{1}{r_i} \quad (1)$$

where

r_i = light reflectance measured at wavelength i

a_i = light absorbance at wavelength i

The light-absorbance data were then transformed to a binary format that is readable by GRAMS/32 (Galactic Industries Corp., 1996), a spectroscopic software package combining data importing, processing, viewing, organizing, and accessing capabilities, and were normalized using the standard normal variate (SNV) method to remove the effects of light scattering caused by diffused reflection (eq. 2):

$$a_{i(SNV)} = \frac{a_i - \bar{a}}{s} \quad (2)$$

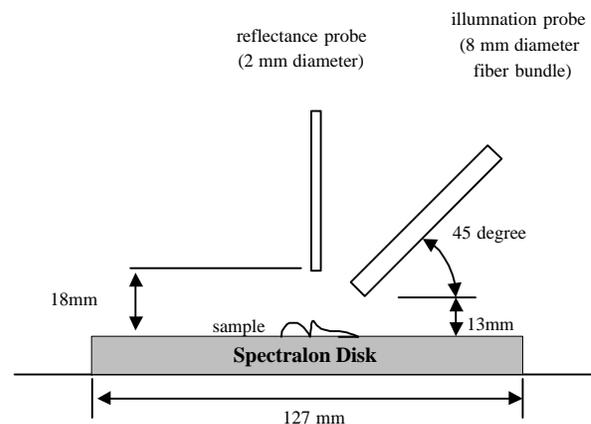


Figure 1. Device used to measure spectral characteristics of plants and soil.

where

- $a_{i(\text{SNV})}$ = normalized light absorbance at wavelength i
- \bar{a} = mean absorbance of the spectrum
- s = standard deviation of absorbance of the spectrum.

SELECTION OF FEATURE WAVELENGTHS

Normalized light absorbance data for three weed species—kochia (*Kochia scoparia*), redroot pigweed (*Amaranthus retroflexus*), and flixweed (*Descurainia sophia*)—and for hard red winter wheat and soil were used in the selection of feature wavelengths. These weed species were the most common in wheat fields, and the colors of their stems were representative of other species. Spectral data from soil and plants planted at different times and measured at different growth stages were divided randomly into two equal-sized sets: the training set for developing the classification model, and the validation set for testing the model. Each set consisted of nine object classes: flixweed leaf, flixweed stem, kochia leaf, kochia stem, redroot-pigweed leaf, redroot-pigweed stem, wheat leaf, wheat stem, and soil. Absorbance spectra of the nine object classes averaged from both training and validation sets are shown in figures 2 and 3.

Five feature wavelengths (496 nm, 546 nm, 614 nm, 676 nm, and 752 nm) within the visible and NIR wavebands were selected using a category-contrast method. Observations of the absorbance spectra of the nine object classes revealed that, at certain wavelengths, the contrasts between major object categories were maximized. Such wavelengths for the contrast between leaf and stem categories were found at 676 nm and 1452 nm. In general,

light absorbance of plant stems is higher at 1452 nm (NIR region) than at 676 nm (red region). To the contrary, the absorbance of plant leaves is generally lower at 1452 nm than at 676 nm. In fact, this trend was observed across the 35 plant species studied, regardless of the stem color.

The contrast in light absorbance between leaves and stems also becomes distinct at 496 nm and 676 nm. The light absorbance of plant stems is generally higher at 496 nm (green region) than at 676 nm (red region), while the absorbance of plant leaves is generally lower at 496 nm than at 676 nm. In this study, 496 nm and 676 nm were selected mainly because of the availability of inexpensive, thin-film, color filters at these wavelengths.

The contrast between green (crop leaves, crop stems, and weed leaves), red (some weed stems), and brown (soil) objects signified at wavelengths 546 nm, 614 nm, and 676 nm. Light absorbance continuously increased from 546 nm to 676 nm for green leaves (wheat and weeds) but decreased for soil. For the reddish stems of kochia and redroot pigweed, the absorbance decreased from 546 nm to 614 nm, reached a minimum value at 614 nm, and increased from 614 nm to 676 nm. The trend for flixweed was slightly different. However, it still was distinguishable from the trend of the leaves and soil. Thus, 546 nm, 614 nm, and 676 nm were selected as feature wavelengths to form two color indices.

Absorbance spectra of soil look completely different from those of plants. A distinct difference between the spectra is that the light absorbances of all plant categories (weeds and wheat, stems and leaves) experience a sharp drop from 676 nm to 752 nm. The decrease between these wavelengths for soil is not significant. Therefore, 676 and 752 nm were

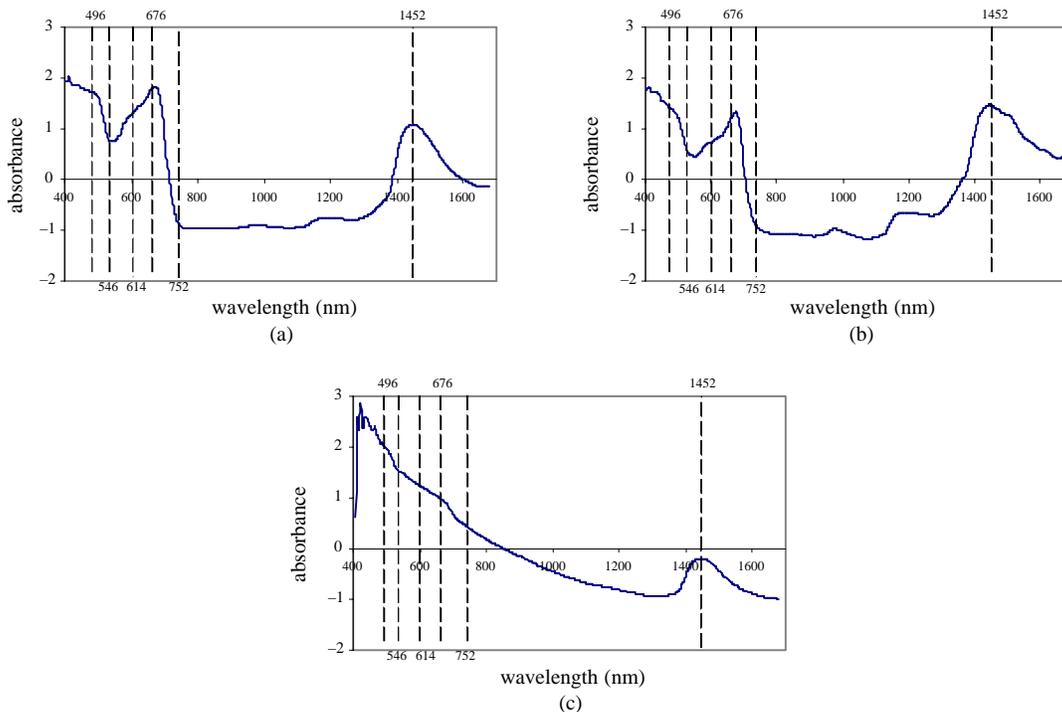


Figure 2. Spectral absorbance of wheat and soil measured using a diode-array spectrometer: (a) wheat leaf, (b) wheat stem, and (c) soil.

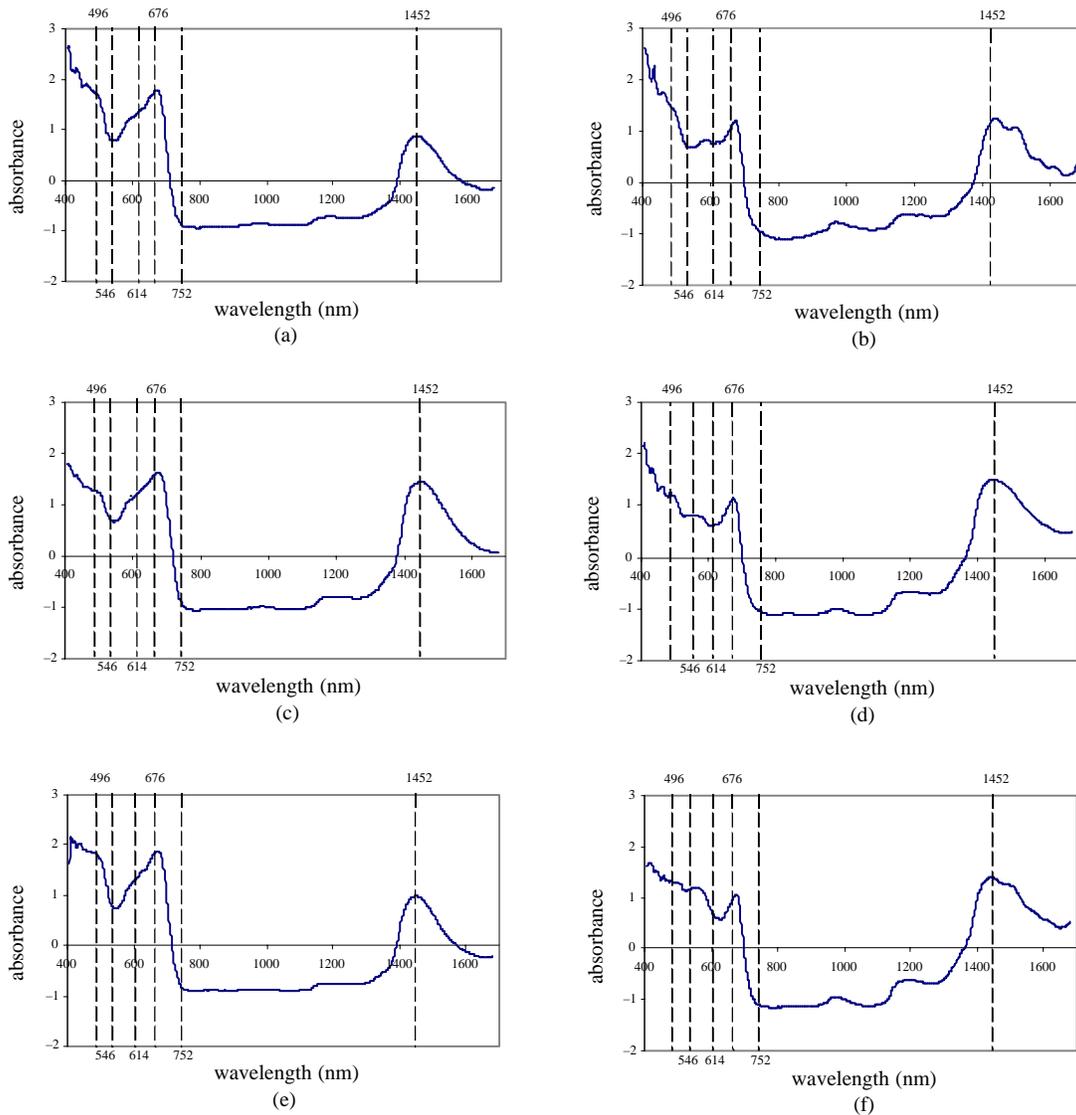


Figure 3. Spectral absorbance of three weed species measured using a diode-array spectrometer: (a) flextweed leaf, (b) flextweed stem, (c) kochia leaf, (d) kochia stem, (e) redroot pigweed leaf, and (f) redroot pigweed stem.

used as the feature wavelengths to construct a color index to categorically differentiate soil from living plants.

COLOR INDICES

Color indices were formed using the feature wavelengths in the form of normalized difference:

$$C = \frac{a_i - a_j}{a_i + a_j} \quad (3)$$

where a_i and a_j are light absorbances measured at feature wavelengths i and j , respectively. The i - j pairs used for four color indices were {614 nm, 546 nm}, {676 nm, 546 nm}, {676 nm, 496 nm}, and {752 nm, 676 nm}.

PARTIAL LEAST-SQUARES CALIBRATION

The partial least-squares (PLS) calibration method was used to decompose the spectra into a set of "variation spectra" that represent the changes in absorbance within the spectral range. PLS performs the decomposition on both spectral and

feature data simultaneously, so that the calibration models established are related directly to the features of interest. In this study, mean values of the color indices for each class were used as the feature data, and the spectra (preprocessed using the SNV procedure at the feature wavelengths) were used as the spectral data to enter the PLS procedure into the GRAMS/32 program. The procedure gave the number of factors used in the calibration model and the predicted color-index values for each sample used in the training.

DISCRIMINANT ANALYSIS

Once the calibration model was established, qualitative DA was used to classify the training spectral data to examine the effectiveness of the model. Entering the DA were the color-index values predicted by the PLS model and the actual classes to which the samples belonged. The predicted, rather than the actual, feature values were used, because the PLS model incorporated statistical variation patterns of the data and, thus, was more robust to noise. The DA gave

indications of the likelihood of each spectrum to match different classes. The class receiving the maximum likelihood was assigned to the spectrum. In this study, DA was performed using the DISCRIM procedure in the Statistics Analysis System (SAS Institute, Inc., 1993).

Table 1 gives the classification results for the training data set. Soil samples were identified correctly with a classification rate of 100%. Classification rates for wheat leaves and stems were 57.5% and 65.5%, respectively. Seventy five percent of kochia stems and 90.9% of redroot pigweed stems were classified correctly; the rest were misclassified as stems of other weed species. When stems of all three weed species were combined into one class, "weed stem", the classification rate reached 88%: 22 of 25 samples were classified correctly as weed stems, and three flixweed stem samples were misclassified as wheat stems.

MODEL VALIDATION

The classification model was also used to predict unknown samples from the validation data set (table 2). Classification results for most classes were similar to those obtained for the training data set; the exceptions were flixweed leaves, redroot pigweed stems, and wheat leaves.

SENSOR DESIGN

The weed sensor consisted of an optical unit, a signal-conditioning unit, an illumination unit, and a data

acquisition unit. A block diagram of the sensor structure is shown in figure 4.

OPTICAL UNIT

Design of the optical unit was based on the feature wavelengths. Six phototransistors installed on a circuit board formed the light detector. Five of the phototransistors had inexpensive, thin-film, band-pass, color filters with central wavelengths equal to the selected feature wavelengths (496 nm, 546 nm, 614 nm, 676 nm, and 752 nm). The sixth phototransistor did not have a filter. Signals from this phototransistor were used to provide reference light intensity. Light reflected from the object passed through a double-convex lens with a focal length of 40 cm before reaching the filters and phototransistors. The distance between the lens and the object also was 40 cm.

SIGNAL-CONDITIONING UNIT

Current signals from the phototransistors were converted to voltage signals using conventional current-to-voltage converters. The signals then were filtered using Butterworth low-pass filters to reduce noise introduced through the light source, power supply, and signal transmission line. The optical unit and signal conditioning circuits were contained in a plastic box, which was painted black.

ILLUMINATION UNIT

The illumination unit consisted of four 50 W tungsten-halogen flood lamps with spherical reflectors. The

Table 1. Classification results for the training set of the spectral data using PLS-DA classifier.

Class		To									
		Fwl	Fws	Kcl	Kcs	Rrl	Rrs	Soil	Whl	Whs	Total
From	Fwl	7 58.3%	1 8.3%	0 0	0 0	3 25%	0 0	0 0	1 8.3%	0 0	12 100%
	Fws	0 0	4 40%	1 10	2 20%	0 0	0 0	0 0	0 0	3 30%	10 100%
	Kcl	0 0	1 20%	4 80%	0 0	0 0	0 0	0 0	0 0	0 0	5 100%
	Kcs	0 0	1 25%	0 0	3 75%	0 0	0 0	0 0	0 0	0 0	4 100%
	Rrl	5 29.4%	0 0	1 5.9%	0 0	5 29.4%	0 0	0 0	6 (35.3)	0 0	17 100%
	Rrs	0 0	0 0	0 0	1 9.1%	0 0	10 90.9%	0 0	0 0	0 0	11 100%
	Soil	0 0	0 0	0 0	0 0	0 0	0 0	5 100%	0 0	0 0	5 100%
	Whl	6 15%	0 0	4 10%	0 0	7 17.5%	0 0	0 0	23 57.5%	0 0	40 100%
	Whs	1 3.5%	4 13.8%	3 10.3%	2 6.9%	0 0	0 0	0 0	0 0	19 65.5%	29 100%
Total		19 14.3%	11 8.3%	13 9.8%	8 6.0%	15 11.3%	10 7.5%	5 3.8%	30 22.6%	22 16.5%	133 100%
Fwl = Flixweed leaf		Fws = Flixweed stem									
Kc = Kochia leaf		Kcs = Kochia stem									
Rrl = Redroot pigweed leaf		Rrs = Redroot pigweed stem									
Whl = Wheat leaf		Whs = Wheat stem									

Table 2. Classification results for the validation set of the spectral data using the PLS-DA classifier.

Class		To									
		Fwl	Fws	Kcl	Kcs	Rrl	Rrs	Soil	Whl	Whs	Total
From	Fwl	2 16.7%	0 0	0 0	0 0	6 50%	0 0	0 0	2 16.7%	2 16.7%	12 100%
	Fws	0 0	4 44.4%	0 0	0 0	0 0	0 0	0 0	1 11.1%	4 44.4%	9 100%
	Kcl	0 0	0 0	5 100%	0 0	0 0	0 0	0 0	0 0	0 0	5 100%
	Kcs	0 0	0 0	0 0	3 100%	0 0	0 0	0 0	0 0	0 0	3 100%
	Rrl	2 12.5%	0 0	1 6.2%	0 0	9 56.3%	0 0	0 0	4 25%	0 0	16 100%
	Rrs	0 0	0 0	0 0	3 30%	0 0	7 70%	0 0	0 0	0 0	10 100%
	Soil	0 0	0 0	0 0	0 0	0 0	0 0	5 100%	0 0	0 0	5 100%
	Whl	3 7.7%	0 0	5 12.8%	0 0	10 25.6%	0 0	0 0	21 53.9%	0 0	39 100%
	Whs	0 0	7 24.1%	0 0	1 3.5%	0 0	0 0	0 0	0 0	21 72.4%	29 100%
Total		7 5.5%	11 8.6%	11 8.6%	7 5.5%	25 19.5%	7 5.5%	5 3.9%	28 21.9%	27 21.1%	128 100%

Fwl = Flixweed leaf Fws = Flixweed stem
 Kc = Kochia leaf Kcs = Kochia stem
 Rrl = Redroot pigweed leaf Rrs = Redroot pigweed stem
 Whl = Wheat leaf Whs = Wheat stem

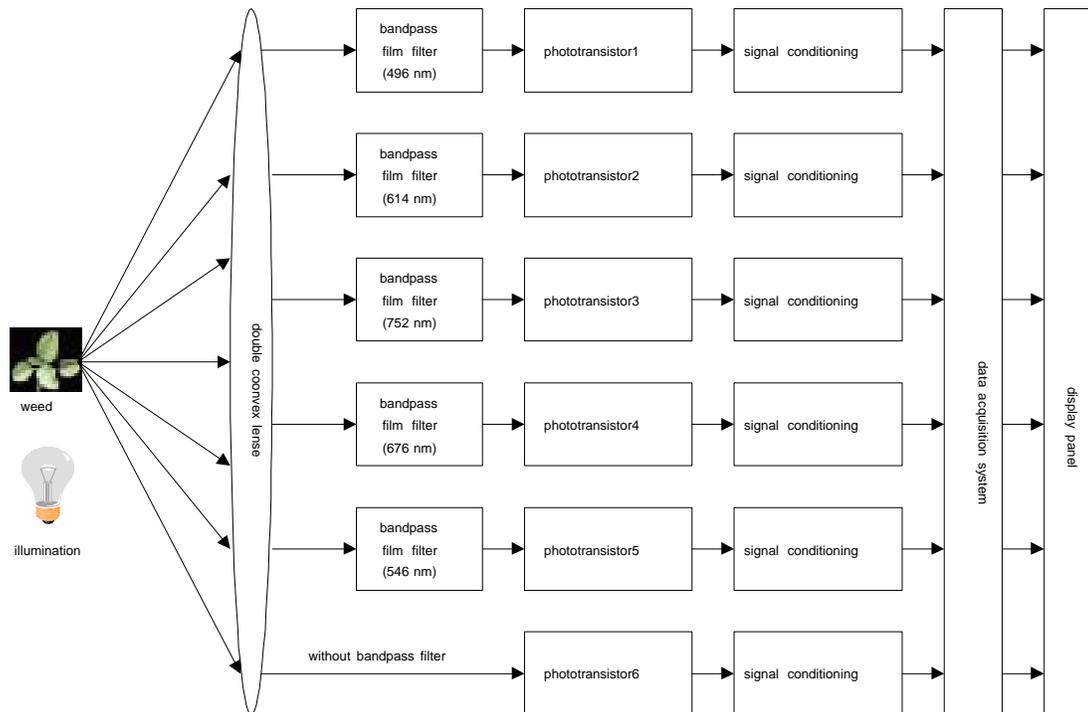


Figure 4. Structure of the optical weed sensor.

lamps were fixed on a special frame so that the light beams joined at the object to be measured. To provide variable illumination intensity, a large-power rheostat was connected in series with the lights to adjust the current.

DATA ACQUISITION UNIT

A DAS 1801ST-DA data acquisition system (Keithley Instruments, Inc., Cleveland, Ohio), installed in a 166 MHz

Pentium computer, and TestPoint software (Capital Equipment Corp., 1995) were employed for the laboratory test. The TestPoint program performed A/D conversion and data processing. The program also displayed the average values and Fourier spectra of the signals. The data were stored in files for further processing.

SENSOR TESTS

Two tests were conducted on the sensor: a color-index test and a weed-density test. Both tests were conducted in a laboratory. The color-index test compared two types of color indices and selected the color index that was less sensitive to illumination variation. The test data also were analyzed to examine the effectiveness of the sensor in detecting weeds. Nine weed species—kochia, flixweed, redroot pigweed, field bindweed (*Convolvulus arvensis*), field pennycress (*Thlaspi arvense*), shepherds purse (*Capsella bursa-pastoris*), joint goatgrass (*Aegilops cylindrica*), Japanese brome (*Bromus japonicus*), and downy brome (*Bromus tectorum*)—as well as hard red winter wheat and soil were used in the test. These weed species are the most common in Kansas wheat fields.

The goal of the weed-density test was to study the ability of the sensor to detect weeds at different weed densities. Five weed species were used in this test—kochia, flixweed, redroot pigweed, field bindweed, and field pennycress. These species were chosen because they were representative of different weed stem colors as well as different foliage shapes. An optical weed sensor measures light reflected from all objects within the sensor's field of view, including weeds, wheat, and soil. The signal from the sensor represents an integral effect of these reflections. If objects with specific color features, such as weeds with reddish stems, are to be detected, the sensor must be capable of extracting this feature from different backgrounds. The factors influencing the sensor signals include: (1) intensity, orientation, and spectral characteristics of the illumination source; (2) position, orientation, and spectral characteristics of the optical sensor; (3) spectral-reflectance characteristics and geometry of the objects to be detected (weeds); (4) spectra-reflectance characteristics and geometry of other objects (crops, weed leaves, soil, and crop residues) in the background; and (5) coverage area of the objects to be detected (weeds) in the sensor's field of view. For the weed density test, the number of weeds appearing in the sensor's field of view was altered, thus changing condition (5), the weed coverage area, while maintaining conditions (1) through (4) basically unchanged.

PLANT SAMPLE PREPARATION

For the color-index test, weeds and crops were planted in small containers in a greenhouse. The diameter of the containers was 12.7 cm, and generally, 10 plants were planted in each container. Thus, the plant density within the container was approximately 0.08 plants/cm². To allow replications of the experiment, five containers were planted for each plant species. Tests were conducted 21 days after the planting date. Samples of kochia, wheat, and bare soil are shown in figure 5.

For the weed-density test, the plant density in a container with 10 plants (0.08 plants/cm²) was defined as the "full"



(a)



(b)



(c)

Figure 5. Samples used in the color-index test: (a) kochia, (b) wheat, and (c) bare soil.

density. "Half" density (0.04 plants/cm²), "quarter" density (0.02 plants/cm²), and single-plant were achieved by manual thinning. Two containers were thinned to each density for each species. Data collected from the two containers were used for training and validation, respectively. Figure 6 shows redroot pigweed at the four densities.

COLOR-INDEX TEST

During this test, the sensor was mounted on a boom, which was installed in front of a test tractor. In order for the sensor to "see" both stems and leaves, it was mounted at an inclination angle of 45° from the ground. The distance between the sensor and the plants was maintained at 40 cm. To avoid any influence of light reflected from surrounding objects, walls were constructed using black boards to make a "dark room" (fig. 7). Wheat, bare soil, and nine species of



Figure 6. Redroot pigweed at different densities: (a) “full” density (0.08 weed/cm²), (b) “half density” (0.04 weeds/cm²), (c) “quarter” density (0.02 weeds/cm²), and (d) single-plant (0.008 weeds/cm²).



Figure 7. Experiment setup for the color-index test.

weeds were tested in a random order. Each test was replicated five times using the five containers, among which three were selected randomly as the training data set and the remaining two as the validation set. The total number of observations collected during the color-index test was 5,413. Each observation included six signals from the six phototransistors. Each signal was averaged from 1,000 readings acquired within a period of 0.1 s. An observation was discarded if the reference light-intensity signal was below a threshold level of 0.5 V. Variable illumination intensity was achieved by changing the resistance of the rheostat, which was connected in series with the lights.

Two types of color indices were compared. Type-I color indices (eq. 4) were in the form of normalized difference and were similar to the color indices given in equation 1:

$$C = \frac{r_i - r_j}{r_i + r_j} \quad (4)$$

where r_i and r_j are reflecting light signals acquired from phototransistors behind the band-pass optical filters with central wavelengths of i and j , respectively. The i - j pairs used for four color indices were {614 nm, 546 nm}, {676 nm, 546 nm}, {676 nm, 496 nm}, and {752 nm, 676 nm}.

The design of type-II color indices considered the effect of “dark current” on the stability of the color indices under varying illuminations. The dark-current effect can be observed in figure 8: the zero light-intensity measurements from two phototransistors did not join at the origin of the

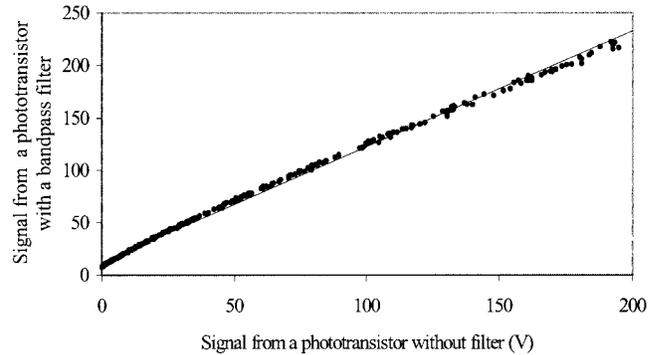


Figure 8. Effect of dark current on phototransistor signals: null-signal points of two phototransistors do not join at the origin. The straight line is the linear regression line.

coordinate system, which was supposed to be the null-signal for both phototransistors.

Type-II color indices were defined as

$$C = (r_i - r_j - b) / r_0 \quad (5)$$

where

r_i and r_j = reflection-light signals acquired from phototransistors behind the band-pass optical filters, with central wavelengths of i and j , respectively.

r_0 = the reflection-light signal acquired from the phototransistor without a filter.

b = the intercept of the linear regression line using r_0 and $(r_i - r_j)$ as the independent and dependent variables, respectively.

The i - j pairs used for type-II color indices were the same as those used for the type-I indices.

The classification model was trained to differentiate three object classes using the training data set: weeds, wheat, and bare soil. Data for nine weed species were grouped as “weeds.” Weed stems and leaves were all included in this class because, in reality, they could not be separated from each other. First, the intercept (b) of each color index was derived through a linear regression analysis between $(r_i - r_j)$ and r_0 using data derived for all object classes. Values of color indices were then calculated for each observation using equation 3. The color-index values and classes were used to enter the DA to establish the classification model. The model was evaluated using the validation data set.

WEED-DENSITY TEST

During this test, soil was used as the background of plants. Wheat and five weed species at four density levels (full, half, quarter, and single-plant) and bare soil were tested in a random order. The test was conducted at variable light intensity. The measurement procedure was identical to that for the color-index test. A total of 5,332 observations were taken.

The classification model was trained using data in the training set at all density levels. The procedure for training was the same as that for the color-index test. The classification model was examined using the validation data set.

RESULTS AND DISCUSSION

COLOR-INDEX TEST

Figure 9 shows the experimental data for a type-I color index. The index value did not remain constant when the illumination intensity varied. When a type-II color index was used, the color index value was stable within a wide range of illumination intensity (fig. 10). Thus, type-II color indices were used to develop the classification model.

The classification results using the training and validation data sets are summarized in tables 3 and 4, respectively. Using type-II color indices, the sensor successfully identified wheat with high classification rates of 98.3% and 83.1% for the training and validation data sets, respectively. The classification rates for weeds were 64.3% and 62.5%,

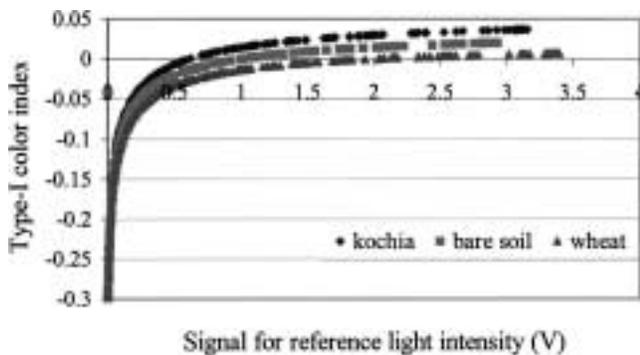


Figure 9. Measured type-I color index.

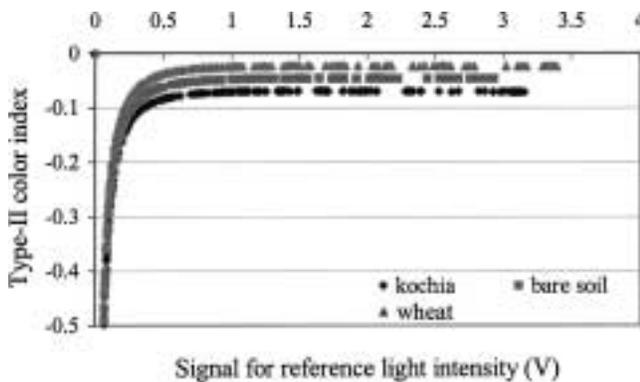


Figure 10. Measured type-II color index.

Table 3. Classification results for the training data set using type-II color indices.

Class		To			Total
		Bare Soil	Weed	Wheat	
From	Bare soil	299 98.7%	4 1.3%	0 0	303 100%
	Weed	501 18.9%	1701 64.3%	444 16.8%	2646 100%
	Wheat	0 0	6 1.7%	338 98.3%	344 100%
Total		800 24.3%	1711 52.0%	782 23.8%	3293 100%

Table 4. Classification results for the validation data set using type-II color indices.

Class		To			Total
		Bare Soil	Weed	Wheat	
From	Bare soil	163 79.5%	42 20.4%	0 0	205 100%
	Weed	543 30.9%	1097 62.5%	115 6.6%	1755 100%
	Wheat	0 0	27 16.9%	133 83.1%	160 100%
Total		706 33.3%	1166 55%	248 11.7%	2120 100%

respectively. These results were derived under a difficult circumstance in which nine weed species with very different spectral characteristics were lumped as “weeds” and the illumination intensity varied over an extremely wide range during the tests. Misclassifications occurred mainly between bare soil and weeds and were probably due to the similarity between the colors of soil and reddish weed stems and, for some samples with small weeds, the large area occupied by soil within the sensor’s field of view.

If the weed species were not grouped, the classifier was forced to identify 11 individual classes (nine weed species, bare soil, and wheat). The results showed that the highest classification rate (73.0%) occurred for redroot pigweed, which was apparently due to its extremely red stems. The classification rates for wheat and bare soil were around 60% and 70%, respectively.

WEED-DENSITY TEST

Results of the density test are summarized in tables 5 and 6. For the training data set (table 5), the classifier trained for three classes (bare soil, weeds, and wheat) successfully classified 100% bare soil (175 observations) and wheat (897 observations) at all four density levels. For weeds at the full, half, and quarter densities, 58.7% of observations were identified correctly at these density levels, and 12.9% were identified as single-plant weeds. Combining these two cases, 71.6% were successfully identified as weeds, and the remaining 28.4% were misidentified as bare soil. Of the 457 observations for single-plant weeds, only 45.8% were classified correctly, and the remaining 54.2% were classified as bare soil. As the density of weeds was reduced, soil covered a larger portion of the sensor’s field of view, and it

Table 5. Classification results for the training data set at four plant densities.

Class			To				Total	
			Bare Soil	Weeds		Wheat		
				wd_fhq	wd_sg	wh_fhq		wh_sg
From	Bare soil		175 100%	0 0	0 0	0 0	175 100%	
		Weeds	wd_fhq	927 28.4%	1913 58.7%	422 12.9%	0 0	3262 100%
	wd_sg		541 54.2%	0 0	457 45.8%	0 0	998 100%	
	Wheat	wh_fhq	0 0	0 0	0 0	723 100%	723 100%	
		wh_sg	0 0	0 0	0 0	0 100%	174 100%	
	Total			1643 30.8%	1913 35.9%	879 16.5%	723 13.6%	174 3.3%

wd_fhq = Weeds at the full, half, and quarter density levels.
 wd_sg = Weeds at the single-plant density level.
 wh_fhq = Wheat at the full, half, and quarter density levels.
 wh_sg = Wheat at the single-plant density level.

became increasingly difficult for the sensor to identify the weeds by color features alone.

For the validation data set (table 6), the classifier again successfully identified all the observations for bare soil. Among the 3,521 observations for weeds at full, half, and quarter densities, 73.8% were identified as weeds, and 26.2% were misclassified as bare soil. Of the 1,028 observations of single-plant weeds, only 41.2% were recognized as weeds, and the rest were misclassified as bare soil. The classification rates for the 730 wheat observations were not as good as those for the training data set. Of the 561 wheat observations at the full, half, and quarter densities, 69.9% were correctly classified, and the remaining 30.1% were misclassified as

bare soil. All the observations for single wheat plants were misclassified as bare soil.

For both training and validation data sets, all misclassifications occurred between plants (weeds and wheat) and bare soil. In no case were weeds misclassified as wheat or wheat misclassified as weeds. This result seemed to be natural, because the plants were surrounded by soil, and reducing plant density enlarged the portion of soil within the sensor’s field of view. The fact that, during the weed-density test, the classifier did not make any mistake between wheat and any of the five weed species tested, even when the wheat and weeds were at similar densities and had similar canopy coverage, was encouraging because it strongly supported the

Table 6. Classification results for the validation data set at four plant densities.

Class			To				Total	
			Bare Soil	Weeds		Wheat		
				wd_fhq	wd_sg	wh_fhq		wh_sg
From	Bare soil		207 100%	0 0	0 0	0 0	207 100%	
		Weeds	wd_fhq	922 26.2%	2296 65.2%	303 8.6%	0 0	3521 100%
	wd_sg		605 58.9%	0 0	423 41.2%	0 0	1028 100%	
	Wheat	wh_fhq	169 30.1%	0 0	0 0	392 69.9%	561 100%	
		wh_sg	169 100%	0 0	0 0	0 0	169 100%	
	Total			2072 37.8%	2296 41.9%	726 13.2%	392 7.2%	0 0

wd_fhq = Weeds at the full, half, and quarter density levels.
 wd_sg = Weeds at the single-plant density level.
 wh_fhq = Wheat at the full, half, and quarter density levels.
 wh_sg = Wheat at the single-plant density level.

hypothesis that differences in spectral characteristics between wheat and weeds can be picked up by the optical sensor.

Although the optical weed sensor detects weeds mainly based on color features, its performance is inevitably affected by other factors, including geometric and morphological factors, of weeds, crops, and soil. When weeds are very small, light reflected from the weed stems contributes very little to the sensor's signal, no matter how distinct the color of the stems may be. For different weed locations within the sensor's field of view, signals received by different phototransistors may vary, causing variations in calculated color indices. This is mainly because of the strong directionality of the phototransistors. Further study is needed to determine the effective sensing area of the sensor and the dependence of the sensor's performance on locations of weeds within the effective sensing area. In addition, the sensor needs to be trained under more difficult conditions, such as low weed densities and mixed wheat and weeds within the effective sensing area, to strengthen the detection power.

CONCLUSIONS

Based on a study of spectral characteristics of weeds, wheat, and bare soil, five wavelengths (496 nm, 546 nm, 614 nm, 676 nm, and 752 nm) were selected as the feature wavelengths for the design of an optical weed sensor. Normalized color indices, compensated for the dark-current effect of the phototransistors, were found to be insensitive to variations in illumination.

When nine species of weeds were grouped as "weeds" to train the sensor, the classification rate of the sensor for the training data set reached 98.3%, 98.7%, and 64.3% for wheat, bare soil, and weeds, respectively. The classification rates for the validation data set were 83.1%, 79.5%, and 62.5%, respectively.

When the weed density was above 0.02 plants/cm², the classifier identified the weeds with classification rates higher than 70% for both the training and the validation data sets. The classification rate reduced to below 50% when only a single weed appeared on the soil background. The remaining weeds were misclassified as bare soil. During the weed-density test, no misclassification between weeds and wheat was found.

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REFERENCES

- Ben, R. J., and J. W. Hamm. 1985. Evaluation of technology required for continuous variation in nitrogen fertilizer application rates: In *Final Report for Engineering and Statistical Research Institute*, 11–30. Contract File No. 01SG. 0196–3–EC43. Agriculture Canada Publication, Ottawa, Ontario, Canada.
- Billier, R. H. 1998. Reduced input of herbicides by use of optoelectronic sensors. *J. Agric. Eng. Res.* 41(4): 357–362.
- Blackshaw, R. E., L. J. Molnar, D. F. Chevalier, and C. W. Lindwall. 1998. Factors affecting the operation of the weed-sensing Detectspray system. *Weed Sci.* 46: 127–131.
- Burks, T. F., S. A. Shearer, and F. A. Payne. 2000. Classification of weed species using color texture features and discriminant analysis. *Trans. ASAE* 43(2): 441–448.
- Capital Equipment Corp. 1995. *TestPoint Techniques & Reference*. Billerica, Mass.
- El-Faki, M. S., N. Zhang, and D. E. Peterson. 1997. Weed detection using color machine vision. ASAE Paper No. 97–3134. St. Joseph, Mich.: ASAE.
- Felton, W. L., and K. R. McCloy. 1992. Spot spraying. *Agric. Eng.* 73(6): 9–12.
- Feyaerts, F., P. Pollet, L. V. Gool, and P. Wambacq. 1998. Sensor for weed detection based on spectral measurements. In *Proceedings of the 4th International Conference on Precision Agriculture*, 19–22 July, St. Paul, Minn..1537–1548. Madison, Wisc.: ASA/CSSA/SSSA.
- Galactic Industries Corp. 1996. *GRAMS/32 User's Guide*. Salem, N.H.
- Lee, W. S., and D. C. Slaughter. 1998. Plant recognition using hardware-based neural network. ASAE Paper No. 98–3040. St. Joseph, Mich.: ASAE.
- SAS Institute, Inc. 1993. *SAS/STAT User's Guide*, Version 6. 4th ed. Cary, N.C.
- Scarr, M. R., C. C. Taylor, and I. L. Dryden. 1997. Automatic recognition of weeds and crops. In *Precision Agriculture 1997. Vol. I: Spatial Variability in Soil and Crop*, 429–437. Oxford, U.K.: Bios Scientific Publishers.
- Shiraishi, M., and H. Sumiya. 1996. Plant identification from leaves using quasi-sensor fusion. *J. Manufacturing Sci. and Eng.: Trans. ASME* 118(3): 382–387.
- Shropshire, G. J., K. Von Barga, and D. A. Mortensen. 1990. Optical reflectance sensor for detecting plants. In *Proceedings of SPIE (The International Society for Optical Engineering): Optics in Agriculture*, 7–8 November, Boston, Mass., Vol. 1379: 222–235. Bellingham, Wash.: SPIE Press.
- Tang, L., L. F. Tian, and B. L. Steward. 1999. Machine vision-based high-resolution weed mapping and patch-sprayer performance simulation. SAE Paper 1999–01–2849. Warrendale, Pa.: Society of Automotive Engineers.
- Thompson, J. F., J. V. Stafford, and B. Ambler. 1990. Selective application of herbicides to UK cereal crops. ASAE Paper No. 90–1629. St. Joseph, Mich.: ASAE.
- Tian, L., J. F. Reid, and J. W. Hummel. 1999. Development of a precision sprayer for site-specific weed management. *Trans. ASAE* 42(4): 893–900.
- Vrindts, E., and J. De Baerdemaeker. 1996. Feasibility of weed detection with optical reflection measurement. In *Proceedings of the Brighton Crop Protection Conference—Pest and Diseases*, 18–21 November, Brighton, U.K., Vol. 1: 443–444. Farnham, U.K.: British Crop Protection Council.
- Visser, R., and A. J. Timmermans. 1996. Weed-it: A new selective weed control system. In *Proceedings of SPIE (The International Society for Optical Engineering): Optics in Agriculture, Forestry, and Biological Processing II*, November, Boston, Mass., Vol. 2907: 120–129. Bellingham, Wash.: SPIE Press.

