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Development of a Spectral-based Weed Sensor

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Summary:
A spectral-based weed sensor was designed based on spectral characteristics of crops, weeds and soil. Light-insensitive color indices were developed. The sensor was tested under laboratory conditions. The detection accuracy for wheat, soil, and weeds reached 98.68%, 98.26%, and 64.29%, respectively.

Keywords: Measurement, Precision agriculture, Sensor, Soil Weeds, Wheat, Weed detection

Spectral-based Sensor Design for Weed Detection

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Introduction

Efficiency of weed control can be improved if herbicides are applied only over the weed-infected areas. To achieve this goal, an accurate weed sensor and associated software are needed. Two popular techniques of weed detection - imaging technique and optical sensors - are being studied. The methods using imaging systems discriminate weeds against soil and crops using shape, texture, or color features. Elfaki et al. (1997) developed a weed detection system using color machine-vision based on relative color indices formed by RGB gray levels. They found that the system was less sensitive to canopy overlay, leaf orientation, camera focusing, and wind effect, compared to systems based on plant shape and texture. Lee and Slaughter (1998) designed and tested a real-time intelligent robotic weed control system for tomato using machine vision. An artificial neural network (ANN) was combined with hardware to classify tomato and weeds. Shiraishi and Sumiya (1996) also develop a machine-vision based plant identification system. Color, aspect ratio, size, radius permutation in leaf profiles, complexity, and curvature were used to identify different plants.

Optical sensors have become another choice for weed detection owing to their low cost, simple system configuration, and high processing speed. Biller (1998) used a commercial optoelectronic system "Detectspray" for detection of weed on soil. The system classified green plants and soil using light reflecting properties of the objects. The amount of herbicides used was reduced by 30% - 70%. Another system, "Spray Vision", sensed reflected light at four different wavelengths - blue, green, red and near-infrared - to detect weeds. Visser and Timmermans (1996) developed a new weed control system using an optoelectric weed sensor. Unlike other systems, the sensor used fluorescence properties to detect weeds. Shropshire et al. (1990) used an optical device to measure the ratio between reflected red and NIR lights for weed detection.

Plant spectroscopic properties were measured for various applications. Wang (1997) conducted research on grain quality measurement using spectral data of grains. Kawamura et al., (1998) used NIR spectroscopy for highly accurate measurement of chemical compositions of rice grains. Reflectance spectral properties were used by Thai et al. (1998) to identify and separate pecan pieces from undesired pecan weevil larvae. A spectral reflectance sensor was built by Sui et al. (1998) to detect nitrogen deficiency in cotton.

This paper reports on the design and preliminary test results of an optical sensor-based weed detection system. The system was designed based on a weed classification model developed by Wang et al. (1998).

The objectives of this research were

1. To develop an optical weed sensor,
2. To define color indices insensitive to variations of the ambient light, and
3. To test the weed sensor under laboratory conditions.

Hardware Design

The weed sensor consists of an optical unit, a signal conditioning unit, an illumination unit, and a data acquisition unit.

Optical unit

The optical unit was designed based on the spectral reflectance characteristics of 31 weed species, five crops, and soil (Wang et al., 1998) within the spectral range of 400 – 1700 nm. The sensor contained phototransistors and color filters with passing bands approximately equal to the selected significant wavelengths. Light reflected from the object to be detected passed through a double convex lens with a focal length of 400 mm before reaching the optical filters and phototransistor (Figure 1). Each sensor output is related to a specific spectral band. An extra channel without optical filter was added to sensing the light intensity.

Signal conditioning unit

Light signals from phototransistors were converted to voltage signals using conventional current-to-voltage converters and were amplified by the signal-conditioning unit. Butterworth low-pass filters were used to reduce noise introduced by light sources, power unit, and signal transmission line. The sensor optical unit and signal conditioning circuits were contained in a black plastic box, which was mounted on a laboratory testing frame. The distance between the lens and the object to be detected was 400mm.

Illumination unit

The illumination unit consists of four 50-Watt halogen-tungsten lamps with spherical reflectors. The lamps were fixed on a special frame so that the light beams joint at the object to be measured. The lamps were used to simulate daylight during the laboratory test. It may also be used as a light source to allow the sensor to work during day or night in the field. A 12V-car battery was used as the power supply for the lamps.

Data acquisition unit

A DAS 1801ST-DA data acquisition system, manufactured by Keithely Instruments Inc., combining with TestPoint software, was employed for the laboratory test. The TestPoint program performed A/D conversion and data processing. The program also displayed the average values of the signals and Fourier spectra of the signals. The data were stored in files for further processing. A 32-bit microcontroller, MC68332 (Motorolor), was also used as a central control unit to control data collection, color index calculation, and display. Functions of on-line calibration and spray control will be added to the microcontroller for upcoming field test.

Laboratory Test Procedures

Sample preparation

Ten weed species - downy brome, field bindweed, kochia, flixweed, sheperds purse, redroot pigweed, joint goatgrass, field pennycress, Japanese brome, and Russian thistle – and wheat were planted in small container in the greenhouse. Five samples were prepared for each plan species.

These weed species were the most popular species commonly seen in Kansas wheat field. Tests were conducted 21 days after the weeds and wheat were planted. Images of kochia, wheat, and soil are shown in Figure 2.

Sensor Testing

Two experiments were conducted. The first experiment used a standard color board and the second used real plants. Both experiments were aimed at observing the dependence of sensor signals on light intensity and finding a set of color indices insensitive to ambient light change.

For both experiments, the same optical sensor and illumination unit was used. To provide variable light intensity, a large power rheostat was connected in series with the lights to adjust the current. The standard color-board calibration experiment was conducted on a test stand as shown in Figure 3 (a). The sensor was placed 400 mm above the test point. Standard color samples (blue, green, and red) were surrounded by black papers. Figure 3 (b) shows the setup for the real plant experiment. The sensor was mounted on a boom which was mounted in front of the test tractor. In order to obtain reflection signals from both stems and leaves, the sensor was mounted with an inclination angle of 35° from the ground. The distance between the sensor and the plants was maintained at 400 mm. To avoid the reflectance from surrounding objects, black boards were used to make a 'dark room' for the sensor. Nine species of weeds were tested in a random order. Each test was replicated five times using five samples. Among five samples for each plant species, Three randomly selected samples were used as the training data set to establish the classification model. The other two samples were later used as the validation data set to verify the classifier.

Results

Test results showed that the normalized differences (Equation 1), which were used in previous studies as the color indices, were very sensitive to light intensity.

$$Normalized\ difference = \frac{channel\ i - channel\ j}{channel\ i + channel\ j} \tag{1}$$

Figure 4 shows that the index changed with light intensity during the standard color board (RGB) calibration test. The indices were adjusted based on light intensity. The new color index takes the following form:

$$color\ index\ i = \frac{channel\ i - channel\ j - constant}{light\ \ intensity} \tag{2}$$

It was found that, if the constant was selected properly, the color index becomes insensitive to the change of light intensity. Values of a modified color index obtained during the real-plant experiment were shown in Figure 5. It was obvious that there were no significant changes in the index when light intensity changed above a threshold value.

The number of observations collected during the real plant test was 5,413, of which 3/5 of data were used for training. The trained classification model was tested with the remaining 2/5 data. For discriminant analysis (DA), all weed species were grouped to 'weed'. Thus, the classifiers were trained to differentiate three classes: weed, wheat and soil. The results of classification were shown in Table 1 and Table 2. Table 1 gives the classification results for the training data set, whereas Table 2 reports the results for the validation data set. Using the new color indices, the sensor identified soil and wheat with accuracy rates over 98% and 80% for the training and validation data sets, respectively. Although the weed classification accuracy was as low as 62.51% for the validation data set, the results are encouraging because this accuracy was achieved under a difficult circumstance where nine weed species with very different spectral characteristics were lumped as "weed" and the light intensity varied in an extremely wide range during the tests. We believe that, from the practical point of view, these results are significant.

If the weed species were not grouped, the classifiers were forced to identify eleven classes (nine weed species, soil and wheat). The results showed the highest classification accuracy (73%) occurred for Redroot Pigweed, which was probably due to the extremely red stems of this species. The classification accuracy for wheat and soil were around 60% and 70%, respectively.

Conclusions

1. The optical weed sensor designed in this study was capable of discriminating soil and wheat against most of weed.

2. The color indices developed in this study were more insensitive to light intensity than previously used normalized differences.

3. When nine species of weeds were grouped as 'weed' to train the classifier, the classification accuracy for the training set reached 98.3%, 98.7%, and 64.3% for wheat, soil and weed, respectively. The classification accuracies for the validation data set were 83.1%, 79.5%, and 62.5%, respectively.

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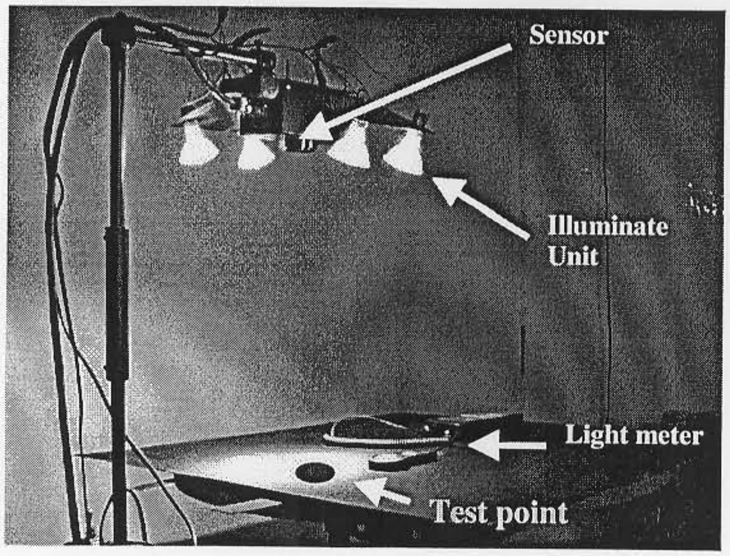
Table 1 Classification results using the training data set

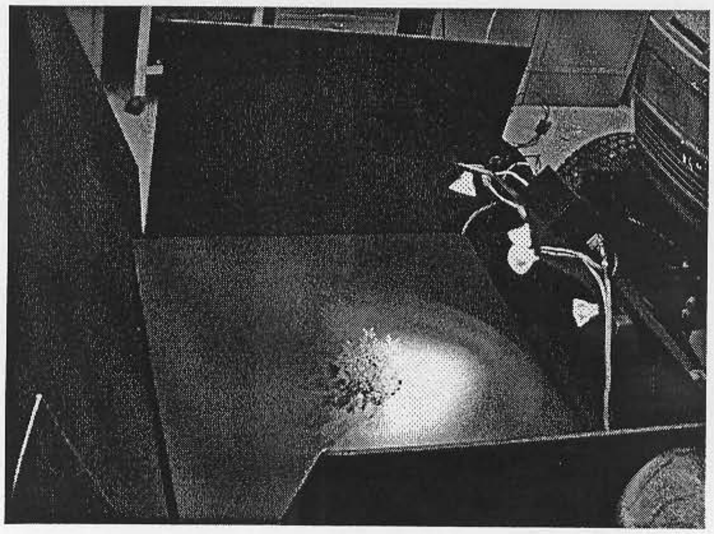
Variety	Soil	Weed	Wheat	Total
Soil	**299** **98.68%**	4 1.32%	0 0	303 100%
Weed	501 18.93%	**1701** **64.29%**	444 16.78%	2646 100%
Wheat	0 0	6 1.74%	**338** **98.26%**	344 100%
Total Percent	800 24.29%	1711 51.96%	782 23.75%	**3293** **100%**

Table 2 Classification results using the validation data set

Variety	Soil	Weed	Wheat	Total
Soil	**163** **79.51%**	42 20.40%	0 0	205 100%
Weed	543 30.94%	**1097** **62.51%**	115 6.55%	1755 100%
Wheat	0 0	27 16.88%	**133** **83.13%**	160 100%
Total Percent	706 33.33%	1166 55%	248 11.7%	**2120** **100%**



(a)



(b)

Figure 3 a. Experiment setup for the standard color board tests
b. Experiment setup for the real plant tests

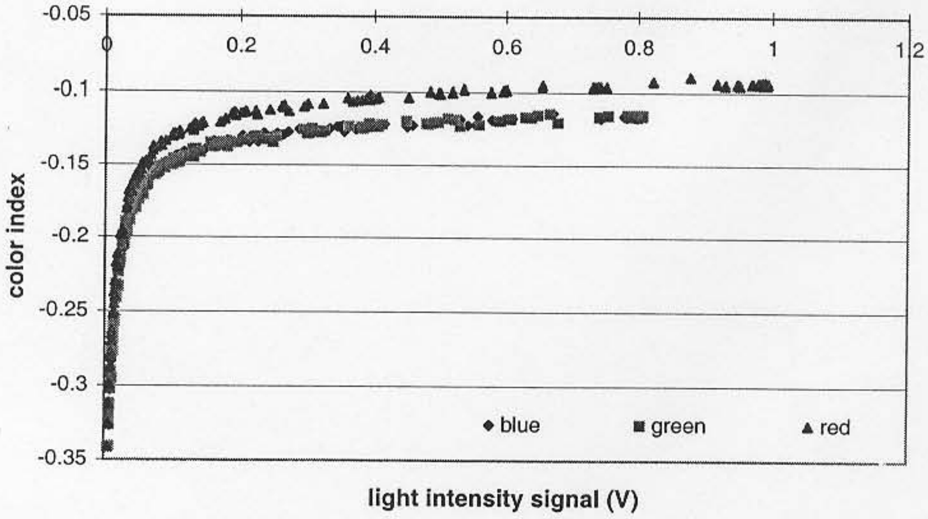


Figure 4 Color index using normalization difference

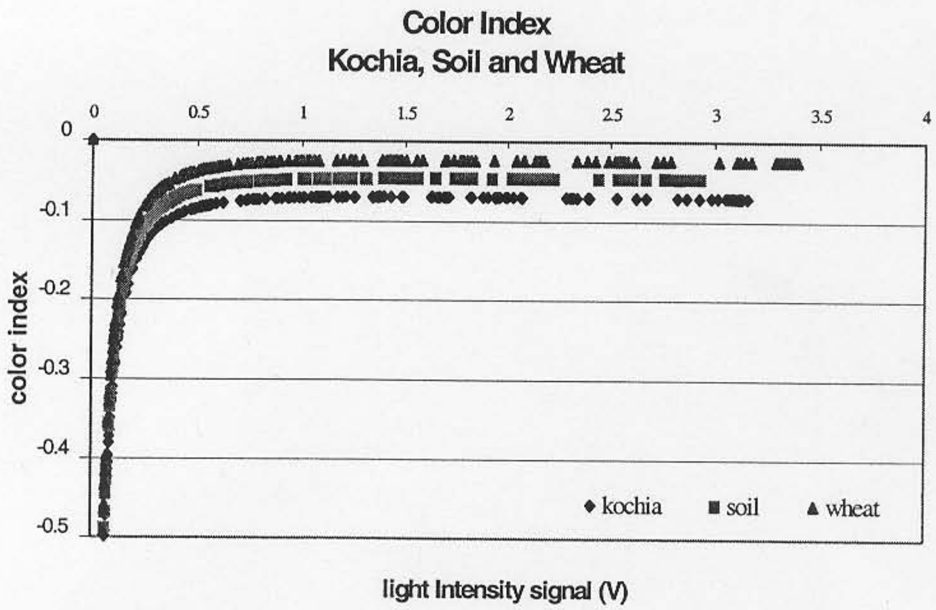


Figure 5 Modified color index