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Multispectral Machine Vision Identification of Lettuce and Weed Seedlings for Automated Weed Control

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Multispectral images of leaf reflectance in the visible and near infrared region from 384 to 810 nm were used to establish the feasibility of developing a site-specific classifier to distinguish lettuce plants from weeds in California direct-seeded lettuce fields. An average crop vs. weed classification accuracy of 90.3% was obtained in a study of over 7,000 individual spectra representing 150 plants. The classifier utilized reflectance values from a small spatial area (3 mm diameter) of the leaf in order to allow the method to be robust to occlusion and to eliminate the need to identify leaf boundaries for shape-based machine vision recognition. Reflectance spectra were collected in the field using equipment suitable for real-time operation as a weed sensor in an autonomous system for automated weed control.
Nomenclature: Lettuce, *Lactuca sativa* L. 'Capitata' and 'Crispa'.
Key words: Machine vision, multispectral images, reflectance, robotics, weed detection, weed recognition.

Despite its federal classification as a minor crop in the United States, lettuce production makes a significant contribution to the economy of California, the country's largest agricultural producer. Approximately 72% of the U.S. crisphead lettuce is produced in California, where it ranked 10th in the state's farm commodities in 1999 with a farm gate value of over $767 million.

Most lettuce in California is planted using direct seeding techniques. The small seed size of lettuce and its shallow planting depth result in the situation where frequent irrigation is needed, which provides ideal conditions for weeds to emerge simultaneously with the crop plants. This situation can have a significant detrimental impact on crop yield if timely weed control is not implemented. Previous studies have documented the yield loss associated with weed competition in a number of crops. Season-long weed competition from mixed stands of grass and broadleaf weeds at 65 weeds/m^2 resulted in complete yield loss of lettuce in England (Roberts et al. 1977). Season-long weed competition with greater than 25% weed cover in California lettuce fields resulted in lettuce yield losses in excess of 50% (Lanini and Le Strange 1991). Weed competition also can have a detrimental effect on lettuce quality (Shrefler et al. 1996) and weeds can be a source of insect pests (van Emden 1965).

Current weed control methods used in California lettuce production include a combination of preemergence herbicide application, mechanical cultivation, and hand hoeing. Vargas et al. (1996) found that hand-hoeing crews mistake weeds for crop plants or miss weeds and eliminate only about 65 to 85% of the weeds on average. In addition, in-row hand hoeing is costly, over five times more expensive than conventional tractor-mounted cultivation (Chandler and Cooke 1992). Because of a lack of viable alternatives, the California lettuce industry is heavily dependent on existing herbicides. However, increasing environmental concerns and regulations such as the U.S. Food Quality Protection Act could force changes in the availability of herbicides.

Research has been conducted to develop highly precise automated weed control systems for row crops ranging from precision autoguidance systems capable of high-speed close cultivation to robotic systems for in-row weed control. The concept of a general agricultural robot for autonomous real-time intra-row weed control is shown in Figure 1. Such a device typically requires four key technologies: guidance, detection, mapping, and precision weed control (Slaughter et al. 2008). Of the four, guidance, mapping, and precision weed control methods are commercially available or are at an advanced stage of development.

Real-time detection of weeds in the seedline remains the main challenge to the commercialization of a general-purpose robotic weed control system for row crops, despite considerable prior research. Four basic techniques have been attempted for noncontact machine vision sensing of plant species in row crops: leaf or plant shape, leaf or plant texture, color or spectral reflectance, and context or plant spacing. Some studies (Burks et al. 2002; Woebbecke et al. 1995) have demonstrated the feasibility of plant species recognition using machine vision systems based on leaf or plant shape where leaf occlusion is minimal, or plant texture in monospecies images. However, the performance of these techniques is significantly degraded for multispecies images containing occluded or damaged leaves typically encountered on commercial farms (Franz et al. 1991).

Pixel-based techniques (color or spectral reflectance) for automated plant species identification have the advantage of being more robust to occlusion (where some parts of the plant are hidden from view) than the leaf or plant shape-based methods investigated previously. Although reflectance-based methods cannot identify the species of hidden foliage, they can be used to identify plant species associated with visible pixels in mixed species scenes with weed/crop occlusion. Pixel-based techniques are also less computationally intensive than shape-based or texture-based methods that have been studied. In a study of color images of 587 plants (36.5% sugar beets,

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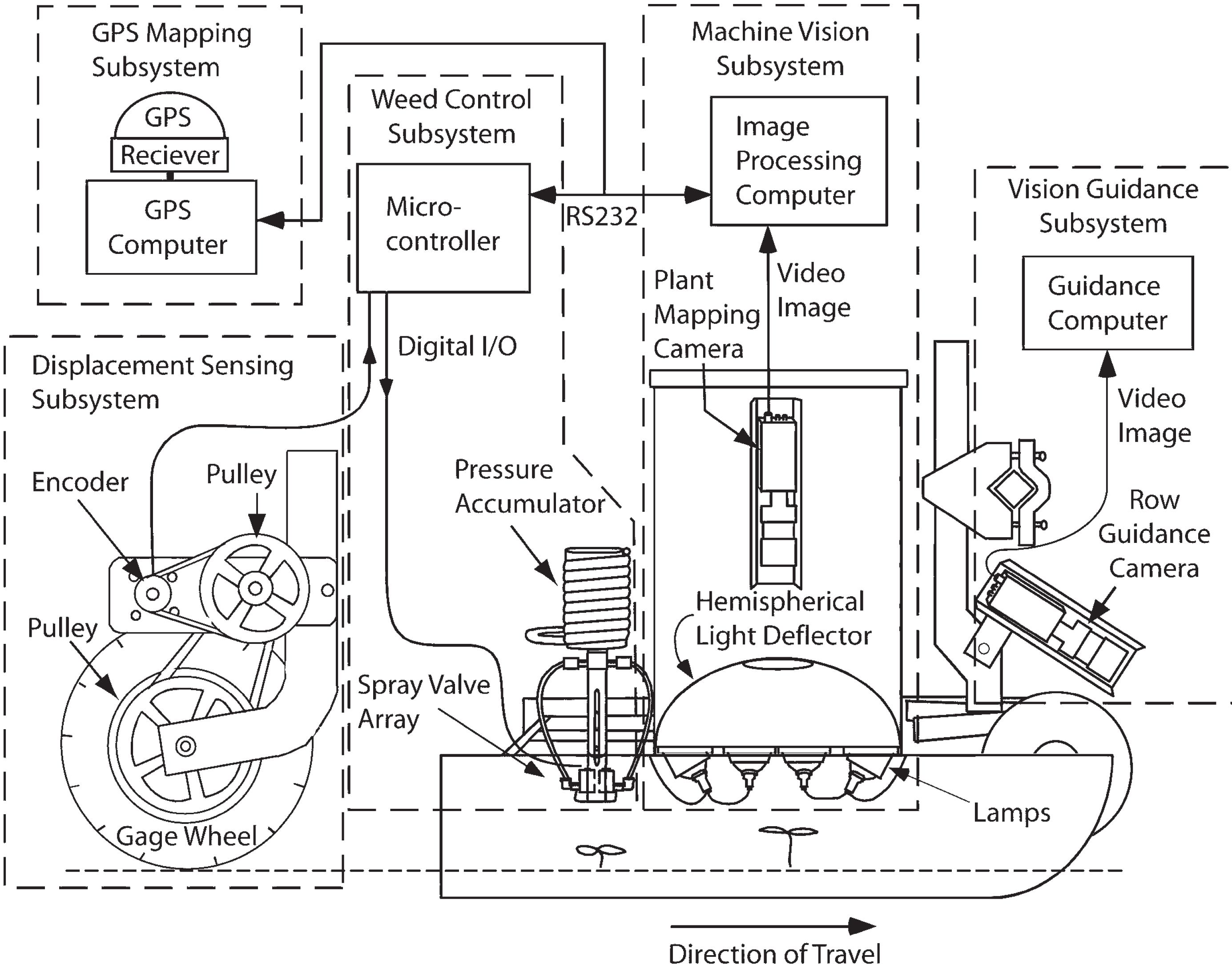

Figure 1. General autonomous real-time intra-row weed control system concept.

Beta vulgaris L., and 63.5% weeds) acquired in different commercial sugar beet fields, Åstrand and Baerveldt (2002) found that normalized green color (G/[R + G + B]) alone successfully classified 91% of the plants into crop and weed categories. Other studies have not been as successful using simple color parameters to identify weeds vs. crop plants (e.g., El-Faki et al. 2000a,b). A few studies (e.g., Gray et al. 2007; Henry et al. 2004; Yang et al. 2004) have investigated the use of multiple vegetation indices (simple ratios of spectral reflectance values; Scotford and Miller, 2005) for species recognition with good results.

A number of studies have looked to narrowband multispectral leaf reflectance techniques to distinguish crop from weed plants. In a study of five potato (*Solanum tuberosum* L.) plants, 12 sugar beet plants, and 25 to 30 of each of three weed species, Borregaard et al. (2000) achieved a crop vs. weed classification accuracy of 89% to 94% using narrowband reflectance at 694 nm and 970 nm. Slaughter et al. (2004) developed reflectance classification models for 400 plants in the same taxonomic family (Solanaceae) showing that color-based models were 75% accurate, and narrowband hyperspectral models in the visible spectrum were 95% accurate in distinguishing tomato (*Lycopersicon esculentum* L.) from nightshade weeds. Hutto et al. (2006) used 21 spectral bands between 378 and 1,000 nm to differentiate six common turfgrass and four weed species and achieved classification accuracies ranging from 52 to 98%. Vrindts et al. (2002) developed a classifier based on reflectance at 11 wavebands in the visible and the near infrared (NIR) region between 480 nm and 820 nm collected from field-grown plants (970 sugar beet spectra and 1,975 weed spectra) using natural illumination. The classifier distinguished sugar beets plants from weeds at 95% and 84% accuracies, respectively. Vrindts et al. (2002) also demonstrated how unstable natural illumination could adversely affect classification accuracies in a similar study of 815 maize (*Zea mays* L.) spectra. Identification of maize spectra as "crop" decreased from 84% to 15% as lighting conditions changed between the times the calibration and validation spectra were collected. Zwiggelaar (1998) reviewed several studies regarding the use of spectral properties for discriminating crop plants from weeds and observed that although there was evidence that spectral properties can be used to discriminate between a certain set of crops and weeds, frequently unique wavebands are selected for classifying specific species. This suggests that site-specific calibration techniques might be required to distinguish crops from weeds using spectral reflectance.

The objective of this research was to determine the feasibility of using visible and near infrared reflectance spectroscopy in the 384 to 810 nm region to distinguish crisphead and leaf lettuce foliage from weed foliage grown under direct-seeded field conditions. Controlled illumination was used to create a stable lighting condition independent of variations in natural illumination. Equipment suitable for real-time field operation was used to collect hyperspectral images. To allow the method to be robust to occlusion and to eliminate the need to identify leaf boundaries, classification models were made using spectra from a very small section of the leaf rather than from whole leaves.

Materials and Methods

The crop plants used in this study were planted using conventional direct seeding methods in mid-August 2004. Hyperspectral images of approximately 150 plants at the second true leaf stage of growth were collected a few weeks later. The plants were grown outdoors on 1-m raised lettuce beds at a University of California experiment station in Salinas, CA. Five species were present in the field and the resulting hyperspectral image database had the following species distribution: crisphead or iceberg lettuce (*Lactuca sativa* L., var *capitata*) 37.5%, leaf lettuce (*L. sativa* L., var *crispa*) 26.5%, common groundsel (*Senecio vulgaris* L.) 11.5%, shepherd's-purse (*Capsella bursa-pastoris* L.) 13.8%, and sowthistle (*Sonchus* spp. L.) 10.7%.

The hyperspectral images were collected using a temperature controlled camera[1] equipped with a transmission grating,[2] lens,[3] and blue filter.[4] The transmission grating provided a raw spectral resolution of 0.41 nm per pixel across the visible and near infrared region from 384.4 to 810.1 nm. To improve the signal to noise ratio, increase the data transfer rate from the camera to the computer, and reduce the data storage requirements, the image data were binned (adjacent pixel information is automatically combined) inside the camera before transfer to provide a 348 by 260 by 12-bit hyperspectral image. The resulting images had a 0.435 mm spatial resolution across the seedline and a 1.64 nm spectral resolution. The images were corrected for dark signal noise, normalized using a reference standard and converted to absorbance units (optical density [OD]) and stored for off-line processing. The plants were illuminated using a fiber optic light line equipped with a tungsten-halogen bulb.[5] The width of the fiber optic light line extended 5 cm beyond each side of the camera's field of view in order to minimize illumination edge effects caused by the fiber's light emission angle, provide a more uniform illumination level, and better maintain the signal-to-noise ratio across the seedline. The blue filter was used to improve the uniformity of the signal-to-noise ratio across the spectrum, which is typically biased toward the red and near infrared portions of the spectrum due to the output characteristics with Tungsten-halogen illumination sources. The hyperspectral camera and illumination system were mounted in an enclosed chamber mounted on a wheeled cart that was manually propelled through the field at a continuous speed of about 25 mm/s. A total of 7,114 hyperspectral images of crop and weed plants were analyzed in this study. Although not required for successful operation, each hyperspectral image contained only one plant species to better facilitate the ground truth labeling and to allow automated recording of the plant species at each pixel in each of the 7,114 images.

The lettuce field in this study was irrigated using sprinkle irrigation. Preliminary research indicated that this type of irrigation method frequently results in small amounts of soil being deposited on the surface of some of the leaves of some seedlings. Leaves were not cleaned prior to image collection; consequently, the spectra of some leaf pixels might have been distorted by the presence of small amounts of soil. To minimize the spectral distortion due to this condition and to reduce other sources of noise in the data, the hyperspectral images were smoothed using a 7 pixel (3 mm) running average in the spatial direction and a 13 pixel (21.3 nm) Savitzky-Golay quadratic smoothing operation was used in the spectral direction (Savitzky and Golay 1964; Steinier et al. 1972).

Vegetation indices (consisting of simple reflectance ratios of two wavebands) and multivariate classification models (using three or more wavebands) were investigated for their ability to distinguish lettuce from weeds. Two vegetation indices (Scotford and Miller 2005), the Red Ratio Vegetation Index (RVI) (Jordan 1969), and the Normalized Difference Vegetation Index (NDVI) (Tucker 1979), were evaluated. Zwiggelaar (1998) has suggested these indices might be useful in distinguishing between weeds and crops. Yang et al. (2004) reported good results (85% classification accuracy) utilizing NDVI for weed vs. crop discrimination in an airborne remote sensing study.

For the multivariate classifiers, two waveband selection techniques were evaluated. The first method used stepwise discriminant analysis to select specific wavebands for classifying the species studied. In the second method, an abridged spectrophotometer model was used with 25 uniformly spaced (every 16.4 nm from 400 nm to 794 nm) wavebands. The waveband spacing was selected to minimize spectral multicolinearity, but no attempt was made to optimize the wavebands for the species studied. Multivariate discriminant analysis was conducted to develop Bayesian classification models to discriminate the five plant species studied.

A custom macro program was created to conduct a one-hundred-out internal cross-validation of the classifier using the Discrim procedure in the SAS software package (SAS 2007). One hundred spectra represent about 1.4% of the 7,114 spectra in the study or about two plants. The best wavebands to use for the red and near infrared wavebands used in the RVI and NDVI indices and the appropriate number of wavebands selected using the stepwise method were determined by the model with the minimum total error rate from the cross-validation analysis. Because the overall goal was to develop an automatic weed control system, the classifier, while trained with five species classes, was evaluated for both its ability to distinguish all five species from one another as well as its ability to distinguish crop (crisphead or leaf lettuce) from weed plants.

Results and Discussion

A plot containing the average absorbance spectra collected in the field using the hyperspectral imaging system for the five species studied is shown in Figure 2. Shepherd's-purse and sowthistle show higher average reflectance in the near infrared region between 700 and 800 nm than the other three species. This indicates a difference in their cellular leaf structure. Leaf optical properties studies indicate that leaf reflectance in the near infrared region increases with the number of cell layers, cell size, cell wall orientation, and cell content heterogeneity (Guyot 1990). In the visible region, the absorbance differences between species in the red and blue regions are greater than those observed in the green region between 500 and 600 nm. These differences are most likely due to differences in chlorophyll content, which is known to have absorbance bands in these regions of the spectrum (Hollaender 1956). Spectral differences in the visible region might also be affected by soil mineral deficiencies (Guyot 1990).

The amount of leaf specular reflectance is similar in the visible and near infrared regions (Guyot 1990). Differences in leaf cuticle properties between species can result in differences in their specular reflectance levels. The optical system used in this study was designed to minimize collection of specular reflectance emitted from horizontal surfaces. However, optical data collection from plants in vivo does not allow control of leaf orientation, resulting in possible specular reflectance differences affecting the spectra collected. In general, the lettuce plants in this study had leaf orientations that were greater than the weeds (many of the weeds had nearly horizontal leaf orientations), possibly contributing to some of the spectral differences observed.

Researchers have shown that water stress and damage from insect pests or diseases can also affect the optical properties of plants. For most plants, an extremely severe level of water stress must exist to affect their optical properties in the 400- to 800-nm region (Guyot 1990). The irrigated plants in this study were not subject to water stress and did not appear to be subject to damage due to pests or diseases.

The minimum total classification cross-validation error rate for the Bayesian classification models, developed using wavebands selected using stepwise discriminant analysis, was obtained with a 25-waveband model. Statistical analysis indicated that the cross-validation error rate for models built with 21 to 25 wavebands were not significantly different ($\alpha = 0.05$), thus the results from the 21-waveband model are presented. The total cross-validation error rate of the 25 waveband model selected by the stepwise method was also not significantly different ($\alpha = 0.05$) from that obtained from the 25-waveband abridged spectrophotometer model. These results indicate that the abridged spectrophotometer approach warrants further study in real-time site-specific plant species recalibration applications where it would be advantageous to eliminate any computationally intensive waveband selection processes. In addition, the abridged spectrophotometer model addresses one of the criticisms of hyperspectral plant species classification (e.g., Zwiggelaar 1998) by including wavebands uniformly spaced across the entire spectral region of the sensing system rather than a subset optimized for the particular species studied. This difference might allow an abridged spectrophotometer model to be better suited or more easily adapted to a wider set of species.

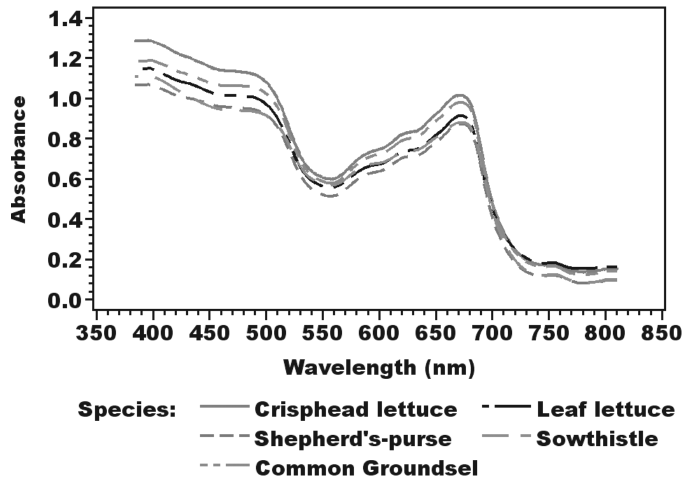

Figure 2. Average absorbance spectra of lettuce crops and annual weed seedlings.

The plant species classification performance of the five species, 21-waveband stepwise model is shown in Table 1. These results are from the cross-validation analysis where the spectra from each plant were omitted from the training process and classified using a discriminant model trained from the remaining plant spectra in the study. The classification accuracy ranged from 75.9% correct for common groundsel to 87.9% correct for leaf lettuce. The largest classification error occurred when 14.3% of the common groundsel spectra were misclassified as crisphead lettuce. In general, misclassified spectra were most frequently categorized as crisphead lettuce (7.5% of spectra) and least frequently misclassified as sowthistle (1.4% of spectra). Approximately 6% of weed spectra were misclassified as other weed species. Of crisphead lettuce spectra, 6.4% were misclassified as leaf lettuce, and 6.1% of leaf lettuce spectra were misclassified as crisphead lettuce. In the context of an automated weed control machine, it is common to apply the same control method to all weeds independent of species. To assess the performance of the classifier in this context, it should be evaluated on its ability to distinguish crop plants from weed plants.

The five-species, 21-waveband stepwise model was re-evaluated in terms of its ability to distinguish lettuce plants from weed plants (Table 2). These results are from a cross-validation analysis where the spectra from each plant were omitted from the training process and classified using a discriminant model trained from the remaining plant spectra in the study. However, in contrast to the species classification results presented in Table 1, it was only considered an error

Table 1. Performance of multispectral machine vision species identification of two lettuce crops and three annual weeds.

Actual species	Classifier's predicted species (% with number of observations below)[a]				
	Crisphead lettuce	Groundsel	Leaf lettuce	Shepherd's-purse	Sowthistle
Crisphead lettuce	**83.0%**	4.9%	6.4%	4.4%	1.4%
	2,214	130	170	117	37
Groundsel	14.3%	**75.9%**	2.1%	6.8%	0.9%
	117	622	17	39	7
Leaf lettuce	6.1%	1.0%	**87.9%**	3.9%	1.1%
	115	19	1,660	74	21
Shepherd's-purse	5.9%	3.8%	4.7%	**82.9%**	2.7%
	58	37	46	811	26
Sowthistle	5.5%	3.8%	2.0%	2.4%	**86.3%**
	42	29	15	18	656

[a] Classification results are from the cross-validation analysis of the 21-waveband stepwise model.

when lettuce plant spectra were misclassified as one of the three weed species, or when one of the three weed plant spectra were misclassified as either of the lettuce species. In this context, the classification accuracy ranged from 83.6% for common groundsel to 94% for leaf lettuce, an increase in performance of about 6% over the individual species classification results. The average classification accuracy for lettuce was 91.3% with an average classification rate of 87.8% for weeds. The overall classification rate was 90.3% for all plants in the study.

The classification accuracy of the multiple waveband models developed in this study compare favorably with those of other published studies. Many of the published ground-based hyperspectral species classification studies have been based upon reflectance spectra collected for controlled leaf orientations and on potted plants. When comparing classification results between studies, it is important to recognize that studies conducted on field grown plants might be more challenging due to specular reflectance effects associated with uncontrolled leaf orientations or field environment effects such as soil deposits on plant leaves. Field-based studies, such as the one reported herein, are important because they provide a more complete assessment of how an agricultural robot for autonomous real-time, intra-row weed control could perform.

The minimum total classification cross-validation error rate for the Bayesian classification models developed using RVI was obtained using 644 nm for red and 810 nm for near infrared. A review of the literature shows that a wide range of wavelength values have been used in determining RVI (e.g.,

Table 2. Performance of multispectral machine vision crop vs. weed classification of two lettuce crops and three annual weeds.

Plant species	No. obs.	Crop/Weed classification accuracy (%)[a]
Crisphead lettuce	2,668	89.4
Common groundsel	819	83.6
Leaf lettuce	1,889	94.0
Shepherd's-purse	978	89.4
Sowthistle	760	92.5
All lettuce	4,557	91.3
All weeds	2,557	87.8
Overall average	7,114	90.3

[a] Classification results are from the cross-validation analysis of the 21-waveband stepwise model.

Biller 1998; Oberti and De Baerdemaeker 2000). Most studies have used wavelengths longer than 810 nm for the near infrared waveband; however, 810 nm was the longest waveband provided by the hyperspectral imaging system used in this study. In general, the classification performance using RVI was poor with a five-species classification rate of 35%. On an individual species basis, the classification accuracy ranged from 16% correct for common groundsel, to 63% correct for sowthistle. In terms of its ability to distinguish lettuce plants from weed plants, the RVI classifier had a total classification rate of 57%.

The results for the NDVI classifier were similar to those found with the RVI classifier. The minimum total classification cross-validation error rate for the Bayesian classification models developed using NDVI was obtained using 640 nm for red and 810 nm for near infrared. The overall classification performance was poor with a five-species classification rate of 38%. On an individual species basis, the classification accuracy ranged from 1% correct for common groundsel, to 71% correct for sowthistle. In terms of its ability to distinguish lettuce plants from weed plants, the NDVI classifier had a total classification rate of 60%.

Clearly the classification rates using single-term vegetation indices to distinguish lettuce from the three weed species studied are not high enough for weed control applications. Yang et al. (2004) distinguished between 11 combinations of corn (*Zea mays* L.) or soybean (*Glycine max* L.) and weeds with classification accuracies of 55% for RVI and 85% for NDVI. Our results for RVI are similar to those obtained by Yang et al. (2004), and our NDVI results were inferior to their results. There are a number of differences between the methods and models used in this study and those used by Yang et al. (2004) that might partially explain the differences in performance. First, the spectra in the Yang et al. (2004) study were collected by airplane at a 1 m by 1 m pixel spatial resolution. At this resolution, the spectra would be a mixture of soil and vegetation and would be more greatly affected by plant shape and structure than the pure leaf spectra collected in this study. Second, Yang et al. (2004) used a decision tree classification method that employed multiple indices (12 for RVI and 65 for NDVI), using a slightly different set of choices for the red and near infrared wavebands in each ratio. The use of a large number of closely related indices eliminates the advantage of simplicity for a single vegetative index and the results might be inconsistent unless the problem of multicolinearity among the closely related indices is addressed. The overall classification accuracy obtained in this study using a 21-waveband Bayesian classification model was superior to the 65-term NDVI decision-tree model used by Yang et al. (2004). Although the airborne weed identification environment is less controlled than the ground-based environment of this study, it is not clear that the additional computational cost of creating a large number of NDVI indices is justified for automated weed identification.

If the 87.8% average weed classification accuracy of the multiwaveband model can be translated into a similar level of weed control efficacy, it shows good potential for a weed sensor in an automated weed control machine. An automated weed control machine with a weed control efficacy above 85% would have superior performance to the weed control achieved with many hand labor crews (Vargas et al. 1996). Further, the classifier developed in this study was based upon the average reflectance spectrum from a 3 mm region of leaf and did not require that the leaf boundary be identified, making it fairly robust to leaf occlusion.

This study has demonstrated the feasibility of using visible and near infrared leaf reflectance imaging techniques to develop an automated site-specific classifier to distinguish crisphead and leaf lettuce from three weed species in a direct-seeded lettuce field. In a crop vs. weed classification mode, the classifier had an average accuracy of 90.3%. Future research should be conducted to study the seasonal variation in optical properties of lettuce and weed species common to commercial lettuce farms to: (1) identify stable waveband differences for discrimination, (2) determine if site specific calibration is needed, and (3) develop automated machine learning methods suitable for site specific calibration needs.

Sources of Materials

[1] Temperature controlled camera, model Photometrics Coolsnap cf monochrome, 12-bit 1392 X1040 CCD sensor, Roper Scientific/ Photometrics, 3440 East Britannia Dr., Tucson, AZ 85706.

[2] Camera equipped with a transmission grating, model ImSpector V8, Spectral Imaging Ltd., Teknologiantie 18 A, 90570 Oulu, Finland.

[3] Camera lens, model C30811, 8.5 mm focal length, Pentax, PENTAX Imaging Co., 600 12th St., Suite 300, Golden, CO 80401.

[4] Camera lens filter, blue filter, model KB12, B+W, Jos. Schneider Optische Werke GmbH., Bad Kreuznach, Rheinland-Pfalz, Germany.

[5] Fiber optic light line, model DCRIII, DDL tungsten-halogen bulb, infrared blocking filter removed, Schott-Fostec., SCHOTT North America, Inc., 555 Taxter Rd. Elmsford, NY 10523.

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