Fuzzy Logic Detection Parameters for Plant Species Identification

Tim Hindman and George E. Meyer
Department of Biological Systems Engineering
University of Nebraska - Lincoln
Lincoln, Nebraska USA 68583-0726

ABSTRACT: Machine vision based on classical and fuzzy image processing techniques has the potential to be a useful tool for plant detection and identification. Plant identification is needed for weed detection, herbicide application, or other efficient chemical spot spraying operations. The key to successful detection and identification of plants by species type is the segmentation of plants from background pixel regions. The segmentation process yields a binary edge image, which contains basic botanical shape information. The binary image provides a template to investigate textural features of plant pixel regions, using nearest-neighbor co-occurrence matrices. Textural analysis uses botanical features such as leaf venation, surface color, and leaf layer structure to identify the species of grass or broadleaf plant. Experiments indicate that red-green-blue (RGB) indices may provide the best segmentation criteria, but these indices work best when based on models of human color perception. However, RGB indices are greatly influenced by intensity and color temperature of the lighting source. Fuzzy membership functions and segmentation procedures were investigated, using color images taken with a digital still camera under various natural and artificial lighting systems. Once clean segmentation is achieved, excellent identification rates of plants can be achieved and tested with statistical discriminant analysis.

KEYWORDS: Plants, Image analysis, Fuzzy logic, Segmentation, Shape, Texture, Color

INTRODUCTION

Research in the area of weed and plant detection has focused on two electronic optical procedures. One procedure detects the presence of a weed using a simple photodiode and optical filter detection methods (*Farm Industry News*, 1997; *Farm Chemicals*, 1997; Hamit, 1999). Another procedure uses machine vision and image analysis to discriminate between crop and weed species (Meyer et al, 1997). The machine vision method is more difficult as it requires plant feature extraction, in the form of shape and textural feature analysis (Meyer et al, 1998a). The feature extraction process is further complicated by the need to segment plant areas from background areas, such as soil, residue, and rocks within the image. Color segmentation is a procedure built into several commercial image processing programs (hard c-means clustering and histogram thresholding). Segmentation errors often show up in grayscale images, as well as any color rasters of red-green-blue (RGB) or hue-saturation value (HSV) images. Moreover, the histogram method usually brings in background pixel errors in multiple modal frequencies. Multiple criteria or indices are therefore needed for successful segmentation of plant regions from background. Use of one specific derived index, *excess green* (2*G-R-B), with successful application of median filters works well in some but not all cases. Excess green segmentation usually identifies 85 per cent or more of the plant pixels (Meyer et al, 1998a; Woebbecke et al, 1995a). Bright background pixels in some color images may contain high green intensities, although not appearing green to the human eye. Murch (1984) indicates that in human visual perception, the retina of the human eye contains 4% blue, 32% green, and 64% red cones, although there is a non-uniform spatial distribution. Meyer et al (1998a) described an *excess red* segmentation procedure that takes into account rod and cone proportions for red and physiological green.

Methods for fuzzy color classification have been described in the literature. In general, fuzzy c-means clustering has been suggested as a method of obtaining segmented object membership functions from color images (Moghaddamzadeh et al, 1998; Lim and Lee, 1990). However, color alone is misleading unless the ambient lighting factors and object reflectance that generate these colors are fully understood. Colorimetry is the primary tool for studying colors and the color temperature is an important aspect of the illuminant (Glad, 1991; Miller and Schneider, 1993; Ross, 1995). Also, fuzzy c-means clustering can potentially involve huge data sets of features derived from images.

Once plant pixel regions are identified with the computer, classical shape and textural feature analyses can be performed. Shape feature analysis has been used with some degree of success to identify plant types. Guyer et al (1986) used four shape parameters to evaluate binary images of leaves of eight different plant species. Guyer's methodology was successful in identifying an individual plant from a set containing two separate species, but individual species identification was not achieved. Guyer et al (1993) further developed shape feature analysis methodology by attempting to build a rule-based knowledge system to simulate human interpretation of shape features. The study used 17 basic primitive features based primarily on plant morphology. Individual species were classified with a success rate of 69 percent, compared to 65 percent for a group of human evaluators. Accuracy would therefore be considered low. Woebbecke et al (1995b) used five dimensionless shape features obtained from near-binary plant images to separate monocots from dicots. These features were shown to effectively separate individual monocot species from all dicot species after approximately ten days after emergence for a three-week growing period. No attempt was made to distinguish between individual species. Yonekawa et al (1996) applied five simple dimensionless shape factors, as shown in Figure 1, to a set of idealized leaf image shapes consisting of 28 overall leaf and petal types, seven leaf lobe and three compound leaf types, and twelve leaf margin types. The system successfully distinguished among sixteen overall leaf and petal types, ten leaf lobe and three compound leaf types, and eight leaf margin types for a theoretical success rate of only 38 percent.

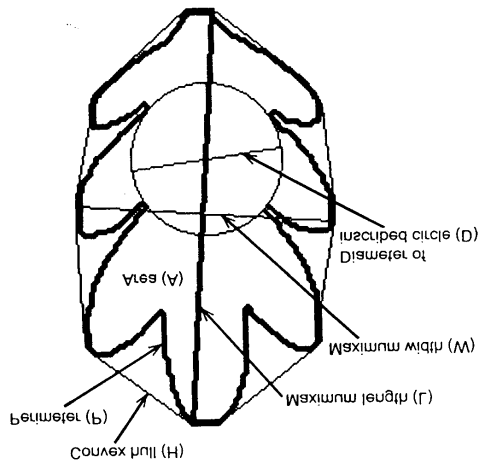


Figure 1: Shape features of a leaf (after Yonekawa et al, 1996).

Gerhards et al (1993) acquired Fourier transforms and shape parameters for leaf images from ten weed species commonly found in cereal crops. The methodology was applied to binarized images of each species at several growth stages. The success rate for individual species identification ranged from 41 to 100 percent, with an average accuracy rate of 81 percent.

Textural feature analysis has more recently received significant attention as a means of plant species identification. Haralick (1979) provided the basis for various statistical and structural approaches to textural features in image analysis, which included optical transforms, digital transforms, textural edginess, structural element, gray tone co-occurrence, run lengths, and so on. Haralick also developed probability definitions that apply to the statistical nature of texture as a surface property. These statistical and structural definitions are used in many image analysis research applications. Shearer and Holmes (1990) used color co-occurrence matrices based on hue, saturation, and intensity for weed detection. Co-occurrence matrices define the spatial dependence of gray tones within an image. Plants were isolated with small manually placed windows and backgrounds were carefully controlled. Individual cultivar samples were successfully classified with an accuracy rate of over 90 percent. Meyer et al (1998b) used four statistical texture measurements to distinguish between broadleaves and grasses. An automatic soil-background segmentation method based on excess green was used to isolate plant areas from background. This was followed up with digital filtering to clean up each area. The result was a binary template image used to guide the calculation of the grayscale co-occurrence matrices independently for plant and background. Even so, this methodology was only successful in separating broadleaves and grasses, probably due to the poor quality of photographic images. Individual plant species were not determined.

Review of the literature indicates a range of plant identification success rates from 40% to 90%. This indicates that there remains a random element of the machine vision process that has not yet been fully investigated. The most serious problem in shape and textural feature analysis is extraneous pixels that are picked up from the background. These extraneous details show up in either black and white or color images. Only when Shearer and Holmes (1990) manually forced analysis of plant pixels did the textural identification success rate appear to increase. The sole use of textural features has been somewhat discouraging, as results are different for various studies according to species, surface topography, and plant canopy features. Most traditional botanical keying procedures involve shape features of individual leaves. In general, a rigorous database of combined shape and textural features needs to be investigated to rank the importance of each feature.

Consequently, one of the main problems in plant image analysis is the isolation or segmentation of the plant surface from the background region of the image. Segmentation problems include chromatic adaptation, which describes the ability of the segmentation system to adapt to variations in color due to changes in lighting conditions. Another problem is how to encode the color. The two primary choices are red-green-blue (RGB) or hue-saturation-value (HSV) color separations. Hue and saturation components have reduced textural details. Only the value component has significant textural detail. Human perception of color is quite different than current computer algorithms in that humans require complimentary colors to bring out details.

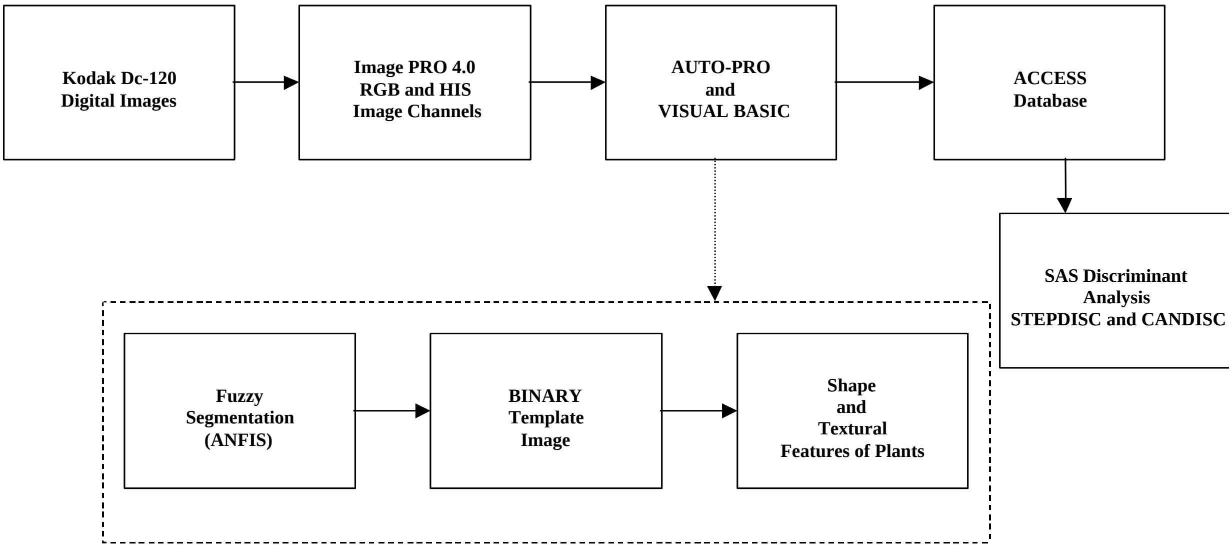
The objective of this paper is to present an application of fuzzy logic techniques for determining factors which affect color segmentation in plant and soil images.

MATERIALS AND METHODS

A Kodak DC-120 digital camera was used to obtain uncompressed electronic images of grass, bare soil, and crop residue, using both natural lighting and a controlled lighting room with a standard photographic copy stand. A barium sulfate reference panel was also used to approximate the color response of the light source. Digital resolution was 25 dots/inch with a width of 1280 pixels and height of 960 pixels. Various lighting sources were used, including daylight blue fluorescent, halogen, and three colored incandescent lights. Color temperature was measured with a Minolta IIIF color meter for each set of images. Light intensity was measured with a General Electric foot-candle meter. The automatic exposure setting of the camera was used. The DC-120 auto exposure setting automatically adjusted for light from f2.5 to f21.4 at shutter speeds up to 1/500 of a second. The main issue here was that one could not ascertain an acceptable tonal range in the images without using the automatic exposure control. Tests were conducted to see if the camera removed the lighting intensity effect and to what extent the camera adjusted for color temperature.

Digital images were transferred from the camera to a Dell Dimension XPS R400, 400 MHz, Pentium II computer with 128 megabytes of random access memory, running Windows NT 4.0 Workstation®, for image, c-means cluster, fuzzy logic, and statistical analysis. Original images were saved as 24-bit color JPEG files on CD-ROM. Membership functions for pixel segmentation were developed through manual inspection, fuzzy c-means using the Adaptive Neuro-Fuzzy Inference System (ANFIS) function in the Fuzzy Logic Toolbox of MATLAB® (The MathWorks, Inc., 1998), and SAS® stepwise and canonical discriminant analysis (SAS Institute Inc., 1990). For leaf segmentation, computed feature data for each leaf would be stored as a record in a Microsoft Access® database. Each set of feature data would then be statistically analyzed for clusters using the SAS STEPDISC and DISCRIM discriminant analysis procedures. Figure 2 is a diagrammatic representation of the overall image analysis scheme used for plant species identification. The binary image provides shape features and a template for the texture analysis.

Figure 2: Image analysis methodology.



SEGMENTATION BETWEEN LEAF AND SOIL BACKGROUND

Several approaches to segmenting the leaf from the soil background have been considered for obtaining a binary template image. One method is to use a threshold value such that all pixels with greater value are selected as leaf (white) and all pixels with less value are taken as soil background (black). This is done after analyzing the histogram. Segmentation based on individual RGB and HSV color channels was considered. Two derived indices have been used to achieve segmentation. One of these is *excess green*, defined as 2*G-R-B. The other is *excess red*, defined as 1.3*R-G. Figures 3 and 4 show a comparison of excess green and excess red segmentation methods. The excess red method did identify part of a leaf in the upper right hand corner of the image. Both plant red and blue values are about 60 percent of the green pixel intensity.

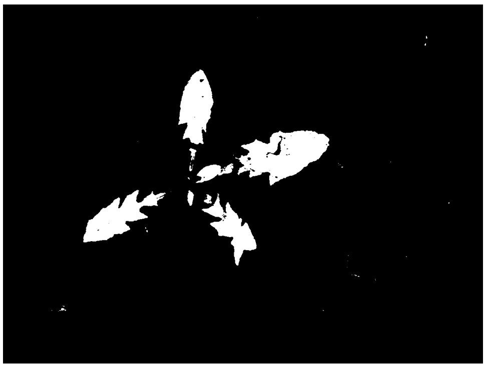


Figure 3: Excess green binarized image of dandelion.

Figure 4: Excess red binarized image of dandelion.

Another solution is to analyze all of the candidate objects and develop shape selection criteria. With this approach, the outlines or boundaries of all candidate "leaf" objects are identified using the automatic color segmentation method in Image-Pro® 4.0. All outlines are saved and analyzed for size using code written in Microsoft Visual Basic. The outline with the largest area is selected and assumed to be the leaf or plant. The excess green value is then calculated for that outline. If the outline is a leaf, the object is then painted or filled with white pixels leaving the remaining area black as the background to create the binary template image.

FUZZY LOGIC APPLICATION

A preliminary fuzzy inference system was developed using the ANFIS function in MATLAB. A set of 84 images was selected as a training set. These images consisted of barium sulfate, grass, bare soil, and corn and wheat residue. Natural lighting conditions included full sun, full shade, cloudy, and early morning sunlight. Daylight blue fluorescent, halogen, and three colors of incandescent artificial light sources were also used. The Sugeno-type fuzzy inference system consisted of seven input variables (exposure time, source intensity, apparent source and target color temperatures, and average RGB color indices) for each image. Each input had three Gaussian membership functions. A single output variable was defined with constant value membership functions determined by ANFIS. An additional 853 images were used as a checking data set to limit the effects of model overfitting. The training process used a hybrid method consisting of backpropagation in combination with a least squares analysis. The model was trained over 40 epochs and evaluated using the combined set of training and checking images to determine the accuracy of the final model.

As a check on the accuracy of the fuzzy logic model, the input data were analyzed statistically using SAS. The STEPDISC procedure is used to perform a *stepwise discriminant* analysis. STEPDISC uses forward selection, backward elimination, or stepwise selection of quantitative variables to determine statistical significance for discriminating among several classes. The DISCRIM procedure in SAS computes various discriminant functions for classifying observations into groups based on the specified variables. This procedure also performs a canonical discriminant analysis, computes squared Mahalanobis distances, and does both univariate and multivariate one-way analyses of variance. Output data sets containing canonical coefficients and scores on the canonical variables are created. The DISCRIM procedure provided a summary of the classification accuracy for each target material and the corresponding error estimates.

RESULTS AND DISCUSSION

Results of the fuzzy logic model analysis are summarized in Table 1. The training data set displayed a 100% accuracy rate as shown in Figure 5, as opposed to a classification rate of 67% using the SAS discriminant analysis. The success rate for individual background material classification ranged from 46 percent to 84 percent, with an overall success rate of 62.5%. The corresponding classification rates for the SAS analysis are summarized in Table 2 and range from 47 percent to 98 percent, with an overall success rate of 70 percent.

Table 1. Classification Summary for ANFIS Fuzzy Logic Model

	Number of Observations and Percent Classified Into MATERIAL:					
From MATERIAL	Barium Sulfate	Bare Soil	Corn Stalks	Grass	Wheat Straw	Total
Barium Sulfate	**69** **64.49**	7 6.54	4 3.74	18 16.82	9 8.41	107 100.00
Bare Soil	42 20.00	**115** **54.76**	38 18.10	9 4.29	6 2.86	210 100.00
Corn Stalks	14 5.98	26 11.11	**130** **55.56**	20 8.55	44 18.80	234 100.00
Grass	36 26.67	13 9.63	6 4.44	**62** **45.93**	18 13.33	135 100.00
Wheat Straw	9 3.59	8 3.19	5 1.99	19 7.57	**210** **83.67**	251 100.00
Total	170	169	183	128	287	937
Percent	18.14	18.04	19.53	13.66	30.63	100.00
Priors	0.2000	0.2000	0.2000	0.2000	0.2000	
Error Count Estimate for MATERIAL:						
	Barium Sulfate	Bare Soil	Corn Stalks	Grass	Wheat Straw	Total
Rate	0.3551	0.4524	0.4444	0.5407	0.1633	0.3912
Priors	0.2000	0.2000	0.2000	0.2000	0.2000	

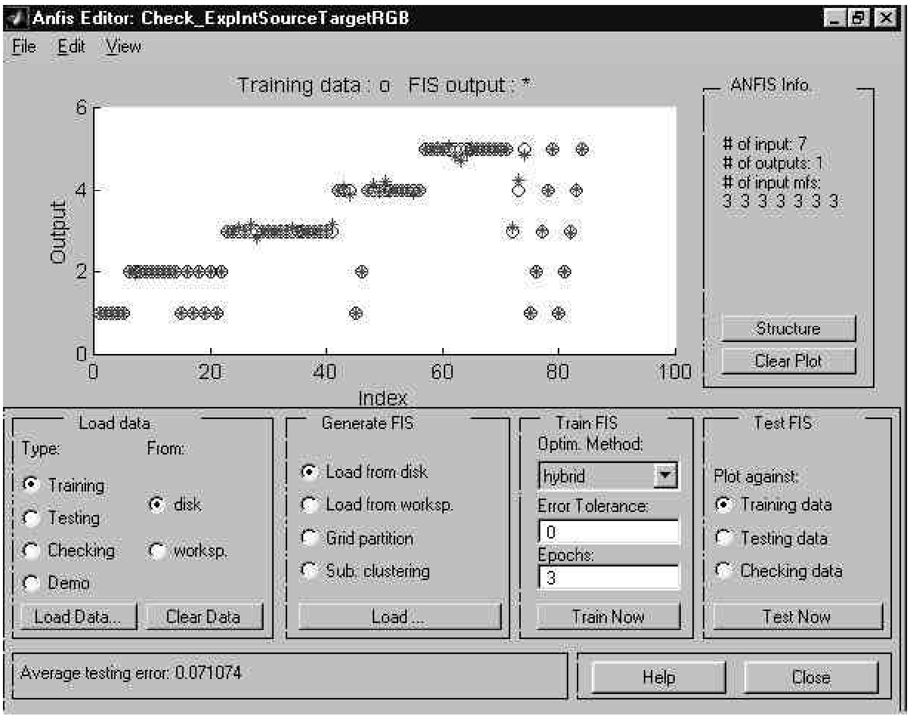


Figure 5: Evaluation of fuzzy inference system model using training data set.

Table 2. Classification Summary for SAS DISCRIM Discriminant Model

	Number of Observations and Percent Classified Into MATERIAL:					
From MATERIAL	Barium Sulfate	Bare Soil	Corn Stalks	Grass	Wheat Straw	Total
Barium Sulfate	**71** **66.36**	14 13.08	3 2.80	4 3.74	15 14.02	107 100.00
Bare Soil	0 0.00	**158** **75.24**	36 17.14	0 0.00	16 7.62	210 100.00
Corn Stalks	0 0.00	79 33.76	**109** **46.58**	10 4.27	36 15.38	234 100.00
Grass	0 0.00	0 0.00	2 1.48	**132** **97.78**	1 0.74	135 100.00
Wheat Straw	0 0.00	18 7.17	35 13.94	13 5.18	**185** **73.71**	251 100.00
Total	71	269	185	159	253	937
Percent	7.58	28.71	19.74	16.97	27.00	100.00
Priors	0.2000	0.2000	0.2000	0.2000	0.2000	
Error Count Estimate for MATERIAL:						
	Barium Sulfate	Bare Soil	Corn Stalks	Grass	Wheat Straw	Total
Rate	0.3364	0.2476	0.5342	0.0222	0.2629	0.2807
Priors	0.2000	0.2000	0.2000	0.2000	0.2000	

The model used for this study was somewhat limited by the available computer memory and the limitations of ANFIS. Although Analysis was limited to seven input variables by the amount of memory required by the ANFIS analysis, although an additional six inputs were available. A total of 2187 rules were generated, with each rule being assigned a separate output membership function. The ANFIS function does not allow the user to define the number of output membership functions to be used. Therefore an additional processing step was required to evaluate the results of the fuzzy logic analysis. It should also be noted that, although all membership functions were assumed to be Gaussian, inspection of the histogram data for individual images indicates that the red, green, and blue pixel values are not normally distributed.

Overall, the fuzzy logic model produced accuracy results that were comparable to the statistical discriminant analysis. The accuracy of the fuzzy logic model could be significantly improved by adjusting the input membership functions using a clustering method such as the fuzzy C-means method. The membership functions for the RGB color indices should also be changed to more closely reflect the actual distribution of pixel values observed from the image histograms.

ACKNOWLEDGEMENTS

This research is supported in part by a USDA National Needs Ph.D. Fellowship and a USDA Special Water Quality grant. Mention of specific trade names is for reference only and not to the exclusion of others that may be suitable. This article has been approved for publication at this conference by the Agricultural Research Division, University of Nebraska - Lincoln. The authors are George E. Meyer, Professor, and Tim Hindman, Ph.D. Fellow.

REFERENCES

Farm Industry News, 1997, “Smart sprayers ready for rows,” Vol. 30, No. 6, p. 44.

Farm Chemicals, 1997, “A ‘smart’ sprayer,” Vol. 160, No. 9, p. 26.

Gerhards, R., A. Nabout, M. Sokefeld, W. Kuhbauch, and H. A. Nour Eldin, 1993, “Automatische erkennung von zehn unkrautarten mit hilfe digitaler bildverarbeitung und Fouriertransformation (Automatic Identification of 10 Weed Species in Digital Images using Fourier Descriptors and Shape Parameters),” Journal of Agronomy and Crop Science, Vol. 171, No. 5, pp. 321-328.

Glad, F. A., 1991, “Color Temperature Alignment using Machine Vision,” IEEE Transactions on Consumer Electronics, Vol. 37, No. 3, pp. 624-628.

Guyer, D. E., G. E. Miles, M. M. Schreiber, O. R. Mitchell, and V. C. Vanderbilt, 1986, “Machine Vision and Image Processing for Plant Identification,” Transactions of the ASAE, Vol. 29, No. 6, pp. 1500-1507.

Guyer, D. E., G. E. Miles, L. D. Gaultney, and M. M. Schreiber, 1993, “Application of Machine Vision to Shape Analysis in Leaf and Plant Identification,” Transactions of the ASAE, Vol. 36, No. 1, pp. 163-171.

Hamit, F., 1999, “Machine Vision for Farming: Recognize weeds - and kill them,” Advanced Imaging, May, p. 39.

Haralick, R. M., 1979, “Statistical and Structural Approaches to Texture,” Proceedings of the IEEE, Vol. 67, No. 5, pp. 786-804.

Lim, Y. W., and S. U. Lee, 1990, “On the Color Image Segmentation Algorithm Based on the Thresholding and the Fuzzy c-Means Techniques,” Pattern Recognition, Vol. 23, No. 9, pp. 935-952.

Meyer, G. E., T. G. Franti, and D. A. Mortensen, 1997, “Seek and Destroy: Machine vision identifies weeds for spot spraying,” Resource Magazine: Engineering and Technology for a Sustainable World, ASAE, Vol. 4, No. 12, pp. 13-14.

Meyer, G. E., T. Hindman, and K. Lakshmi, 1998a, “Machine Vision Detection Parameters for Plant Species Identification,” in *Precision Agriculture and Biological Quality*, G. E. Meyer and J.A. DeShazer, Chairs/Editors, Boston/MA, USA, SPIE: The International Society for Optical Engineering, Vol. 3543 (ISBN 0-8194-3155-9), pp. 327-335.

Meyer, G. E., T. Mehta, M. F. Kocher, D. A. Mortensen, and A. Samal, 1998b, “Textural Imaging and Discriminant Analysis for Distinguishing Weeds for Spot Spraying,” Transactions of the ASAE, Vol. 41, No. 4, pp. 1189-1197.

Miller, K. A. and W. E. Schneider, 1993, “Colorimetry: Methods and Tools,” The Photonics Design and Applications Handbook, Pittsfield/MA, USA, Laurin Publishing Company, pp. 39-40.

Moghaddamzadeh, A., D. Goldman, and N. Bourbakis, 1998, “A Fuzzy-Like Approach for Smoothing and Edge Detection in Color Images,” International Journal of Pattern Recognition and Artificial Intelligence, Vol. 12, No. 6, pp. 801-816.Murch, G., 1984, “Physiological Principles for Effective Use of Color,” IEEE CG&A, pp. 49-54.

Murch, G., 1984, “Physiological Principles for Effective Use of Color,” IEEE Computer Graphics and Applications, Vol. 4, No. 11, pp. 49-54.

Ross, T. J., 1995, “Fuzzy Logic with Engineering Applications,” New York/NY, USA: McGraw-Hill, Inc., pp. 388-401 and 430-447.

SAS Institute Inc., 1990, “SAS/STAT User’s Guide,” Cary/NC, USA, Version 6, Fourth Edition, pp. 387-404 and 707-771.

Shearer, S. A., and R. G. Holmes, 1990, “Plant Identification using Color Co-occurrence Matrices,” Transactions. of the ASAE, Vol. 33, No. 6, pp. 2037-2044.

The MathWorks, Inc., 1998, “Fuzzy Logic Toolbox User’s Guide,” Natick/MA, USA, Version 2.

Woebbecke, D. M. G. E. Meyer, K. Von Bargen, and D. A. Mortensen, 1995a, ‘Color indices for weed identification under various soil residue and lighting conditions,” Transactions of the ASAE, Vol. 38, No. 1, pp. 259-269.

Woebbecke, D. M., G. E. Meyer, K. Von Bargen, and D. A. Mortensen, 1995b, “Shape Features for Identifying Young Weeds using Image Analysis,” Transactions of the ASAE, Vol. 38, No. 1, pp. 271-281.

Yonekawa, S., N. Sakai, and O. Kitani, 1996, “Identification of Idealized Leaf Types using Simple Dimensionless Shape Factors by Image Analysis,” Transactions of the ASAE, Vol. 39, No. 4, pp. 1525-1533.