INTERNATIONAL JOURNAL OF AGRICULTURE & BIOLOGY
1560–8530/2006/08–5–602–605
http://www.fspublishers.org

Weed Detection in Sugar Beet Fields Using Machine Vision

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ABSTRACT

Machine vision is a useful method for segmentation of different objects in agricultural applications, especially shape recognition methods, but it has more difficulty for weed detection due to leaves occlusion and their overlaps. Many indices have been investigated by researchers to perform weed segmentation based on color information of the images. In this study the relation between three main components (red, green & blue) of the images, which constitute the true color of different plants have been extracted from image data using discriminant analysis. 300 digital images of sugar beet plants and seven types of common sugar beet weeds at different normal lighting conditions were used to provide enough information to feed the discriminant analysis procedure. Discriminant functions and their success rate in weed detection and segmentation of different plant species have been evaluated.

Key Words: Segmentation; Color; Discriminant analysis; Weed; Sugar beet; Precision farming

INTRODUCTION

Destructive impacts of herbicide usage on environment and water contamination have led to many researches oriented toward finding solutions for their accurate use. If weeds could be correctly detected, patch spraying or spot spraying can effectively reduce herbicide usage as Brown *et al*. (1990) stated that weed control could be maintained with a 25% reduction in herbicide use, if herbicides were applied properly.

Morphological features are used for detection and segmentation of different objects such as pistachio (Ghazanfari *et al*., 1997) and cereal grain classification (Majumdar & Jayas, 2000). Some researchers have also used shape features to distinguish different plants (Franz *et al*., 1991; Guyer *et al*., 1993; Woebbeck *et al*., 1995). These features can only be used when the image includes just one plant in each frame and its leaves do not overlap to make shape recognition possible. Therefore, in real field condition, which plants have overlap or occlusion, shape features cannot easily be used.

Color feature extraction is also used for segmentation of different objects. Some researchers have explored various color spaces such as HSI space (Tang *et al*., 1995) or different composition of color components to define boundaries in which weeds can be segmented from the main crop. Woebbecke *et al*. (1994) examined some color indices to distinguish weeds from the soil and residues. El-Faki *et al*. (2000) have also defined and evaluated some indices for weed detection. Tian *et al*. (1997) used chromaticity components to attenuate the influence of non-uniform lighting. Astrand and Baerveldt (2003) used some combinations of color and shape features for sugar beet weed segmentation. They evaluated shape features for single plants and showed that plant recognition based on color vision is feasible with three features and a 5 -nearest neighbors classifier. Color features could solely have up to 92% success rate in classification. This rate increased to 96% by adding two shape features.

All HSI, YCbCr, YIQ and other definitions of color space in addition to some equations that have been proposed by researchers are based on relations between three main components R, G and B; For example HSI color space is defined because it is more similar to human definition of colors (Gonzales & Woods, 1992). But there is a unique combination of these three main components for each class of different objects that should be found. The objective of this study was to extract the actual relations between three main color components R, G and B, which have constituted weeds and sugar beet classes by means of discriminant analysis.

MATERIALS AND METHODS

A digital camera (FotoClip, 2164) was used to acquire 300 digital images from several agricultural field of Fars province in Iran under various lighting conditions (from sunny to cloudy sky, from morning to afternoon). Images had a resolution of 1600 × 1200 pixels concerning to a field of view of about 70 × 60 cm on the ground and were taken at a distance of about 1.2 m from the soil surface having 24 -bit data field and JPEG format. A computer Pentium 4, 2000 MHz and Image Processing Toolbox version 3.00 for use with MATLAB version 6.5 (Mathworks, 2002) was used for algorithm development. Statistical Package for the Social Sciences (SPSS, 1999) version 9.05 was used for discriminant analysis.

Different light intensity is the major problem in color segmentation schemes because it directly affects on R, G, B, components (El-Faki *et al*., 2000). The strategy in this study was to break up the segmentation algorithm to two separate algorithms; one for parts in light and the second for parts in shadow. If we determine the mean luminance value of the parts in light and in shadow then we can lead each pixel to be processed in the related algorithm, on the basis that its luminance value is larger or smaller than the determined mean value for each group.

Luminance value was calculated separately for parts in the shadow and parts in the light using equation (1) (Gonzales & Woods, 1992):

$$L = (R + G + B)/3 \qquad (1)$$

Where "L "is pixel luminance; R, G and B are red, green and blue components, respectively.

Data collection. For each species of weeds and sugar beet plants, some parts in the light were chosen from the images and R, G, B, values was collected for each kind of plants (Jafari *et al*., 2004). Luminance values were then used in algorithm to separate pixels in light from those in shadow.

Discriminant analysis. Discriminant analysis (DA) is a technique used to build a predictive model of group membership based on observed characteristics of each case. Discriminant functions (DF) are the linear combinations of the standardized independent variables, which yield the biggest mean differences between the groups. In this study, stepwise DA is used to determine each pixel membership to eight groups of plants including sugar beet and seven types of weeds, based on their independent variables (R, G & B). In this study, three different composition of sugar beet against the weeds were considered as below:

a) Classification of sugar beet and weeds. In the first state, 8 different classes including sugar beet and weeds were defined. However, it is not usual to define more than two groups for DA, but this test will yield just one DF, which will reduce the size and processing time of the algorithm. Also the result of classification can be helpful to show the similarity between different weed classes (Jafari *et al*., 2004).

b) Classification of sugar beet versus all weeds. In the second test, whole weed species were collected into one group called "Weeds". So, there are two classes "sugar beet" and "weeds" which must be classified. This test was done to verify the possibility of segmenting the weeds all at once.

Since there are two classes for classification, this test will also yield one discriminant function (DF). If this method is successful, computation and time will be greatly reduced (Jafari *et al*., 2004).

c) Classification of sugar beet versus each weed species one by one. At the third test, sugar beet and each one of the weed species separately gathered into one group for classification. In fact, this test constituted of seven separate tests that each one is classification of sugar beet against one of the seven weed species. Each DA will yield one DF for each group, thus seven DFs will be realized during this test that each one maximizes the distance between sugar beet class and one of the weed species. So, these functions can be used to define whether a pixel is a part of sugar beet or a distinct weed. These functions are denoted by DF. 1 through DF. 7 in this paper and have a form of:

$$DFn = b_1R + b_2G + b_3B \qquad (2)$$

Where DFn is nth discriminant function and b_1, b_2 and b_3 are function coefficients.

Algorithm structure. To define a threshold value for segmentation of pixels in light from those in shadow, the total mean value for luminance was calculated for sunlit pixels and pixels in the shadow. On this basis threshold value for luminance (L_t) was set to 77.5 and the image is processed in the "Sunlit algorithm" after passing through the filter below:

- IF L (i, j) < L_t THEN f (i, j) = 0 ELSE f (i, j) is kept up.

And the same image also is processed in "Shadow algorithm" after passing trough filter below:

- IF L (i, j) > L_t THEN f (i, j) = 0 ELSE f (i, j) is kept up.

Which

L (i, j) is the pixel luminance calculated by equation.1 and f (i, j) is pixel value in image.

Fig. 1 shows the overall procedure for weed segmentation, while the detail of "sunlit" and "shadow" algorithms are shown in Fig. 2. It must be noted, however, that the procedure in this two sub-algorithms is the same, but discriminant functions (DF. 1 through DF. 7) are different for "sunlit" and "shadow" algorithm and they have been extracted from their related lighting condition.

Using excess green method (Woebbeck *et al*., 1995), soil pixels segmented from the images. The first discriminant function (DF. 1) is used to segment the related weed from sugar beet plants. In this stage, other weed plants may be discarded or remain at the result of segmentation, but sugar beet pixels are discarded. For example DF. 1 (concerning to sugar beet & Chenopudim) is:

$$DF\ 1 = 0.371\ B - 0.114\ G \qquad (3)$$

"R" components have had a small effect in classification and so didn't enter in this function. Group centroids for sugar beet and Chenopodium are 1.006 and -0.967, respectively. Therefore, threshold criterion will be:

IF 0.371 B – 0.114 G > 0.0195 THEN f (i, j) = 1 (4)

IF 0.371 B – 0.114 G < 0.0195 THEN f (i, j) = 0 (5).

Such segmentation is done based on other discriminant functions DF 2 through DF 7 and each one of these functions will retain its related weed and omit sugar beet.

Before the final stage, there will be two processed image. "Sunlit algorithm" will result an image that has specified the parts of weeds in the light and such a result will be yield from "Shadow algorithm" for those parts of weeds in the shadow. The final stage "Logical OR" will add the result of these two algorithms and will paste segmented weed parts in the light to the segmented weed parts in the shadow and yield a complete weed image.

Fig. 1. Weed segmentation procedure

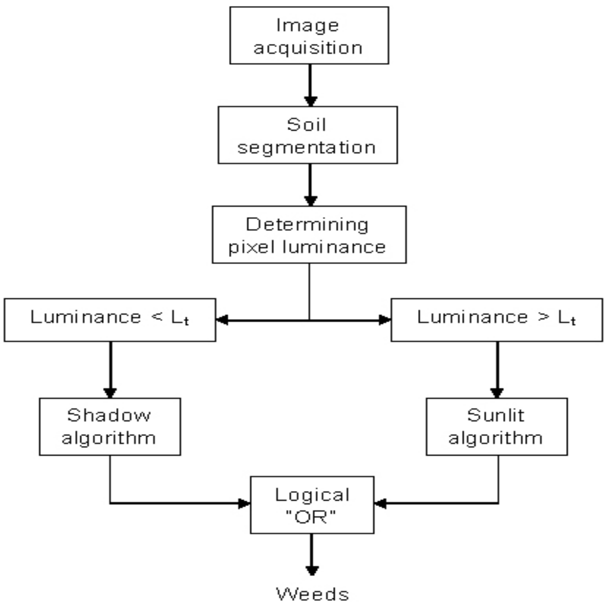
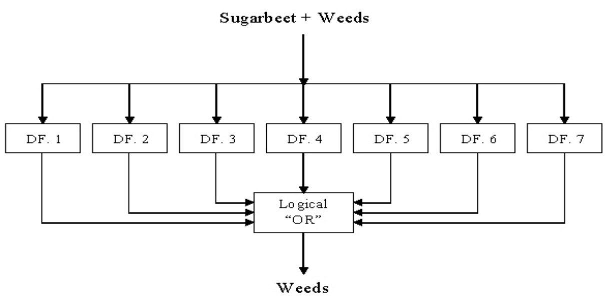


Fig. 2. Sunlit (and Shadow) algorithm



RESULTS AND DISCUSSION

Comparing the results in light and shadow showed that correct classification rate (CCR) for parts in light is more than parts in shadow. It is interesting that when 2 classes are defined (sugar beet versus weeds) overall classification rate is more than the case when they are broken up to 7 classes. It is due to low CCR of some weeds that don't have enough similarity to other members in the class and do not completely satisfy in their relation. Here, Portulaca in sunlight and Convolvulus in shadow have this situation so were put in separate class and collect all other the weeds into one class for sunlit algorithm and such a manner was done for Convolvulus in shadow algorithm. Thus, for each sub-algorithm two DF will be extracted that is smaller than algorithm with seven DF and also has more CCR. This test has been done and a classification rate of 88.5% was achieved for all weeds except Portulaca in sunlight and 88.1% for weeds except Convolvulus in shadow. The results are given in Table I.

On this basis, the proposed algorithm will have "sunlit" and "shadow" sub-algorithms such as Fig. 3 instead of Fig. 2.

Table I. Classification of sugar beet versus all weeds but *Portulaca*

		Predicted Group Membership		
	plants	sugar beet	Weeds	Total
%	sugar beet	78.3	21.7	100.0
	Weeds	9.7	90.3	100.0
88.5% of original grouped cases correctly classified				

Fig. 3. Improved "Sunlit" (and "Shadow") algorithm

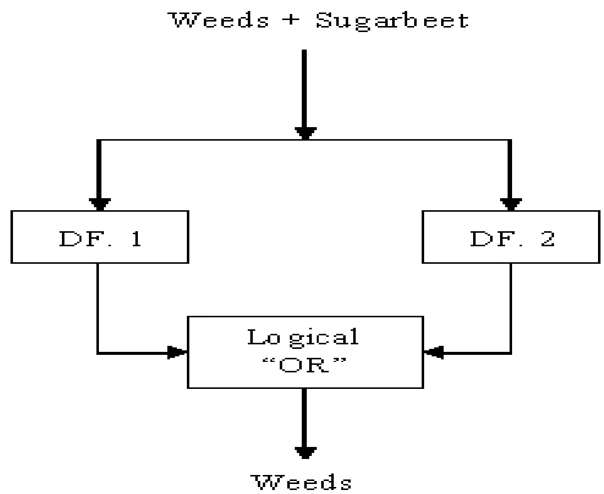


Fig. 4. Weed segmentation (a) main image (b) segmentation result

Fig. 4 Shows the final classification result, while sugar beet, Chinese Lantern plant (*Physalis alkekengi* L.), Little Hogweed (*Portulaca oleracea* L.) and Barnyard grass (*Echinochloa crus-gali* (L.) Beauv) exist in the image.

CONCLUSION

Boundaries for color segmentation of different weeds from sugar beet were determined using discriminant analysis. Due to plant occlusion, color features were the only features were extracted for classification. Segmentation success rate based on the extracted discriminant functions was considerable for weeds specified in this study. However it is important that, which type of weed killing device is considered to be used. For spot spraying with selective herbicides, which the main objective is to minimize the herbicide consumption, such classification rates are desirable. But for mechanical weeding device, such as weeder robots, MCR must be a very small value, not to hurt the sugar beet plants. Much works should be done in future to somehow enter shape features into the algorithm, to classify plants based on both shape and color features when occlusion exist. Light and shadow condition has been separated in the proposed algorithm. By such a method, we don't need to find a complicated equation, which can exclude light intensity from the color.

REFERENCES

Astrand, B. and A. Baerveldt, 2003. A mobile robot for mechanical weed control. *Int. Sugar J.,* 105: 1250

Brown, R.B., G.W. Anderson, B. Proud and J.P. Steckler, 1990. *Herbicide Application Control Using GIS Weed Maps*. ASAE Paper No. 90-1061. ASAE, St. Joseph, Michigan, USA

El-Faki, M.S., N. Zhang and D.E. Peterson, 2000. Factors Affecting Color-Based Weed Detection. *Trans. ASAE,* 43: 1001–9

Franz, E., M.R. Gebhardt and K.B. Unklesbay, 1991. Shape description of completely visible and partially occluded leaves for identifying plants in digital images. *Trans. ASAE,* 34: 673–81

Ghazanfari, A., J. Irudayaraj, A. Kusalik and M. Romaniuk, 1997. Machine vision grading of pistachio nuts using Fourier descriptors. *J. Agric. Engg. Res.,* 68: 247–52

Gonzalez, R.C. and R.E. Woods, 1992. *Digital Image Processing.* Addison-Wesley Publishing Co., Reading, Mass., USA

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. *Trans. ASAE*, 36: 163–71

Jafari, A., S.S. Mohtasebi, H. Eghbali Jahromi and M. Omid, 2004. *Color Feature Extraction by Means of Discriminant Analysis for Weed Segmentation*. ASAE Paper No. 043059. ASAE, St. Joseph, Michigan, USA

Majumdar, S. and D.S. Jayas, 2000. Classification of Cereal Grains Using Machine Vision: I. Morphology Models. *Trans. ASAE*, 43: 1669–75

Mathworks, 2002. *MATLAB Image Processing Toolbox. User's Guide Version 3.00*. The Mathworks, Inc., Natick, MA

SPSS, 1999. *SPSS for Windows*. Ver 9.05. SPSS, Inc., Chicago, Ill., USA

Tang, L., L. Tian and B.L. Steward, 2000. Color image segmentation with genetic algorithm for in-field weed sensing. *Trans. ASAE*, 43: 1019–27

Tian, L., D.C. Slaughter and R.F. Norris, 1997. Outdoor field machine vision identification of tomato seedlings for automated weed control. *Trans. ASAE*, 40: 1761–8

Woebbeck, D.M., G.E. Meyer, K. Von Bargen and D.A. Mortensen, 1995. Color indices for weed identification under various soil, residue and lighting conditions. *Trans. ASAE*, 38: 259–69

Woebbeck, D.M., G.E. Meyer, K. Von Bargen and D.A. Mortensen, 1995. Shape features for identifying young weeds using image analysis. *Trans. ASAE,* 38: 271–81

(Received 22 December 2005; Accepted 17 June 2006)