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Crop Detection and Positioning in the Field Using Discriminant Analysis and Neural Networks Based on Shape Features

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ABSTRACT

Development of an autonomous weeding machine requires a vision system capable of detecting and locating the position of the crop. It is important for the vision system to be able to recognize the accurate position of the crop stem to be protected during weeding. Several shape features of corn plants and common weed species in the location were extracted by means of morphological operations. Effective features in the classification of corn and weeds were analyzed using stepwise discriminant analysis. Among the seven features used in the analysis, four were sufficient to classify the two target groups of weeds and corn. These shape features were fed to artificial neural networks to discriminate between the weeds and the main crop. 180 images consisting of corn plants and four species of common weeds were collected from normal conditions of the field. Results showed that this technique was able to distinguish corn plants with an accuracy of 100% while at most 4% of the weeds were incorrectly classified as corn. In the final stage, the position of the main crop was also approximated and its accuracy was measured with respect to the real position of the crop. The position of the crop is necessary for the weeding machine to root up all of the plants except the main crop. It was concluded that the high accuracy of this method is due to the significant difference between corn and weeds in the critical period of weeding in the region.

Keywords: ANN classifier, Crop detection, Image processing, Shape analysis, Weed.

INTRODUCTION

Information on weed distribution in the field is necessary to implement spatially variable herbicide application or other implements to remove weeds from the field. Many types of machine vision technologies have been employed, including spectral devices and digital cameras. Some researchers have proposed different methods for weed recognition among the crops.

Pe´rez *et al*. (2000) developed a near-ground image capturing and processing technique in order to detect broad-leaved weeds in cereal crops under actual field conditions. The proposed method used color information to discriminate between vegetation and background, whilst shape analysis techniques were applied to distinguish between crop and weeds. The performance of algorithms provided an acceptable success rate when assessed by comparing the results with a classification performed by human [7].

Shape features of the radish plant and weed were investigated by Cho *et al*. (2002). They proposed a machine vision system using a charge coupled device camera for the weed detection in a radish farm. Shape features were analyzed with the binary images obtained from color images of radish and weeds. The success rate of recognition was 92% for radish and 98% for weeds [3].

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Weed detection is a complicated task especially in late growing stages of the plants and when different weeds exist in the field. In such situations it is essential to make a decision based on different sources of information. Data fusion enhances the correct discrimination rate of weeds and crops. 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 neighbor's classifier. Color features could solely have up to 92% success rate in classification. This rate increased to 96% by adding two shape features [2].

All colors appearing in the image and captured by common digital cameras are composed of three main color components *i.e.* red, green and blue. By this consideration it seems rational to assume that different objects can be segmented by the percentage of their main color compositions. Jafari *et al.* (2006) extracted the actual relations between the three main color components R, G and B which constitute weeds and sugar beet color classes by means of discriminant analysis. They used digital images of sugar beet plants and seven types of common sugar beet weeds at different normal lighting conditions. Discriminant functions and their success rates in weed detection and segmentation of different plant species were evaluated. Different classification success rates ranging from 77% to 98% were gained [4].

Pan *et al.* (2007) studied the segmentation of weeds and soybean seedlings by their 3CCD images in the field. 3CCD cameras are often used because they can offer more information than ordinary cameras. They used a multi-spectral imager to snap photos of crop and weed in fields, which included one crop and two weeds. Firstly, they segmented soil background by the IR channel distribution plot. Then, they used morphological operations to delete these small sized weeds and extract the soybean image [6].

Texture features of weed species have been applied for distinguishing weed species by Meyer *et al.* (1998). Four classical textural features derived from the co-occurrence were used for discriminant analyses. Grass and broadleaf classification had the accuracies of 93% and 85%, respectively. Individual species classification accuracy ranged from 30% to 77% [5].

Polder *et al.* (2007) used textural image analysis to detect weeds in grass. In the textural analysis, images were divided into square tiles, which were subjected to a 2-D FFT. The power of the resulting spectrum was found to be a measure of the presence of coarse elements (weeds). Application of a threshold made it possible to classify tiles as containing only grass or as containing a weed [8]. They implemented the algorithm of Ahmad and Kondo [1] and found that it performed reasonably well for docks in grass, but at several seconds per image it was too slow to be usable for real-time detection.

Gabor wavelet features of NIR images of apples were extracted for quality inspection and used as input to kernel PCA [10]. Kernel PCA first maps the nonlinear features to linear space and then PCA is applied to separate the image features (solves nonlinearity problems). The PCA transformed data were given as input to a K-nearest neighbor classifier to discriminate healthy apples from blemished ones. Other classification methods such as support vector machine (SVM), PCA, kernel PCA and Gabor PCA were also investigated. However, Gabor wavelet (5 scales and 8 orientations) combined with kernel PCA had the highest recognition rate (90.5%).

In this paper it was assumed that the final weeding machine has to mechanically remove all plants but the main crop. Shape features of the corn plants and weeds were used for the discrimination. Therefore, the main objective was to identify which shape features are more effective in segmentation. Determining the position of the main crop is more critical for mechanical weeding comparing to patch spraying. Thus the vision system must accurately distinguish the main crop stem or the position of the crop.

MATERIALS AND METHODS

Image Acquisition

A digital camera (Canon IXUS) was used to acquire 180 digital images from the agricultural field of Shiraz University situated in the College of Aagriculture. Images were taken at a resolution of 1600×1200 pixels corresponding to a field of view of about 50cm×70cm on the ground at a distance of about 0.7-0.8 m from the soil surface. A computer Pentium IV, 3.42 GHz and Image Processing Toolbox version 6.2 with MATLAB version 7.7 (MathWorks, 2008) was used for algorithm development. The critical period of weeding in the location for direct sowing corn is 25 to 30 days after the emergence. Images were taken in this period from the corn plants and weeds (amaranth (*Amaranthus retroflexus*), camelthorn (*Alhagi maurorum*), pigweed (*Chenopodium album* L.) and field bindweed (*Convolvulus arvensis* L.)).

Soil Removal from the Image

There are three different groups of objects in the images mainly consisting of the background soil, weeds and the crop. The first step is to remove the background soil from the vegetative parts. Studies for plants detection have been performed using different combinations of color components. Some color vegetation indices were investigated which were able to accentuate the plant greenness and attenuate the background color. The Excess Green Index proposed by Woebbecke *et al*. (1995) could reasonably omit background soil from the images as defined by Equation (1):

$$ExcessGreenIndex(ExG) = 2g - r - b \quad (1)$$

Where, r, g and b are the main color components. Threshold value for separating the background and vegetation parts could be set to zero, however due to concerns regarding possible damage to the crop, negligible biases may be acceptable. After this operation images were turned into black and white images referring to background soil and plants, respectively [9]. Figure 1 shows sample images of corn plants and the weeds after following the excess green method.

Mathematical Morphology and Extracting Shape Features

There are recognizable differences between the shapes of the corn and weed plants. The corn has lance shape leaves. Camelthorn is a heavily-branched gray-green thicket with long spines along the branches. Amaranth has oval shape leaves in its early growing stages. The first true leaves of pigweed are ovate in shape, and slightly notched at the tip of the leaf blade while the leaves of field bindweed are

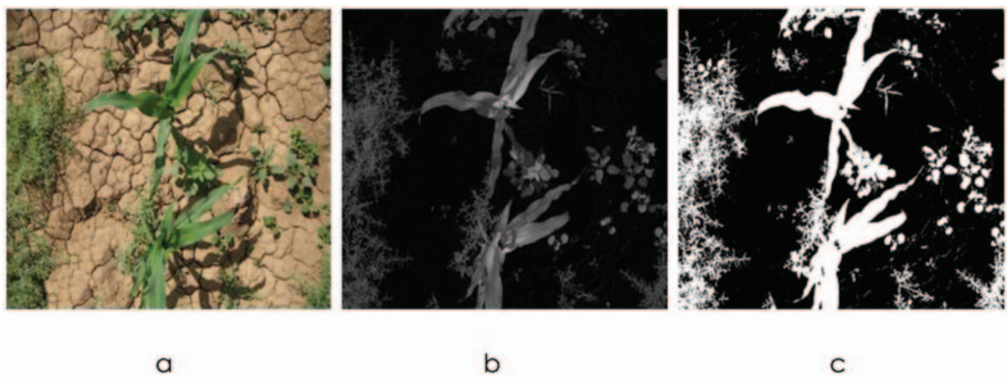

Figure 1. Soil removal using the excess green method a) original image b) excess green c) binary image showing vegetative parts.

arrowhead-shaped with a small petiole.

As it can be seen in Figure 1, there is a significant difference between the sizes of corn leaves and the leaves of the weeds. This was considered as the first step to eliminate the small weeds from the images. Morphological operations comprising sequential erosion and dilation (so called opening) can eliminate the problem of occlusion and partial overlapping of the leaves. Since corn plants were among the biggest objects in the images, the operation was performed on the binary images until five objects were remained, while increasing the number of sequences did not yield a significant improvement in the results.

In the next step, each object in the image was labeled and certain geometrical features of the unconnected objects were extracted using the codes written in Matlab. These features were aspect ratio, compactness, elongation, and perimeter to broadness, length to perimeter, length to width and cube of perimeter to area by length (Table 1).

Discriminant Analysis and Feature Selection

All of the seven features extracted from objects in the images can be used to distinguish corn from the weeds however some features may contain more information than the others. Thus, discriminant analysis was performed to classify individual objects into two groups: 'Corn' or 'weeds'. Processing time would be diminished if the most powerful features were used. Furthermore, previous researches have shown that when the number of training samples is limited, using a large feature set may decrease the generality of a classifier [11]. To select the effective features in the classification of weeds and crops, stepwise discriminant analysis was used.

Artificial Neural Network (ANN)

Back propagation neural networks were used for the classification of weeds and corn plants based on the shape features. Networks were used in two steps to determine if there a significant difference between the classification using all features or using only effective features determined by discriminant analysis. A neural network can be trained to perform a particular function by adjusting the weights. The network is adjusted, based on a comparison of the output and the target, until the network output matches the target.

Table 1. Definitions of shape features.

Shape features	Definition
Aspect ratio	$\frac{\text{Length of major axis}}{\text{Length of minor axis}}$
Compactness	$\frac{100 * area}{perimeter^2}$
Elongation	$\frac{\text{Length of major axis- length of minor axis}}{\text{Length of major axis +length of minor axis}}$
Perimeter to broadness (PTB)	$\frac{\text{Perimeter}}{\text{2(Length of major axis+ length of minor axis}}$
Length to perimeter (LTP)	$\frac{\text{Length}}{\text{Perimeter}}$
Length to width (LTW)	$\frac{\text{Length}}{\text{width}}$
Cube of perimeter to area by length (PTAL)	$\frac{perimeter^3}{100 * area * \text{Length of major axis}}$

Fifty images of corn and 80 images of weeds in the image were used to train the ANN classifier. In the input layer, each input node was assigned to one of the shape features. All ANNs comprised one hidden layer with one to three neurons in the layer. Two neurons were used in the output layer which takes the values of one referring to corn plants and zero referring to the weeds.

The proposed ANN classifier is shown in Figure 2. Log sigmoid transfer functions were applied to each processing element. Training was stopped when the performance goal was met. Achieving the desired MSE of 0.005 was the criterion for stopping the training procedure. Twenty images of corns and 30 images of weeds were used to evaluate the ANN performance after training. Training data were normalized using the minimum and maximum values in each row of the matrix (the features). The equations of normalization were saved to be used for the determination of the actual values of the test set.

RESULTS AND DISCUSSION

Segmentation based on shape features is mostly effective in cases that little overlapping exists between the objects in the image. On the other hand, it is important to kill the weeds within the critical period of weeding. Applications before or later than this period do not effectively reduce the weeds population. The critical period of weeding is related to the location and crop species. Fortunately, the critical period of weeding in the location of this study is from May 10 to 25 while most of the plants are small so that overlapping the leaves rarely occurs. In this situation, extracting the shape feature of the leaves was possible. Adherence of some small weeds to the corn leaves made negligible effect on the location of the plant centroid that was considered in the locating error. It did not have a significant effect on the discrimination of corns from the weed due to the large size of corn leaves comparing to those of weeds survived after erosion–dilation procedure (Figure 3).

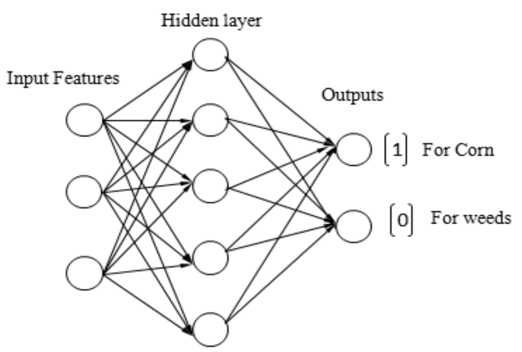

Figure 2. Schematic topologies of the neural networks used.

Values of shape features corresponding to each group i.e. weeds and corn plants are shown in Figure 4. This figure represents the functionality of each feature in classification of these two groups. It is obvious that features with less overlapping are more efficient in separating the weeds and corn plants.

Classification Using Discriminant Analysis

F statistics and Wilks' lambda value are two criteria used to show the significance of a feature in classification. Small F statistics and high values for Wilks'lambda cause a feature to be excluded or included in the discriminant functions.

Stepwise discriminant analysis was able to diminish the size of features from seven to four. It means that to assign each plant to weed or corn groups, four shape features are sufficient. Redundant features were omitted in discriminant functions. Discriminant functions can be used to define the membership of each individual plant to the target groups. Selected features can be seen in Equation 2 while the result of

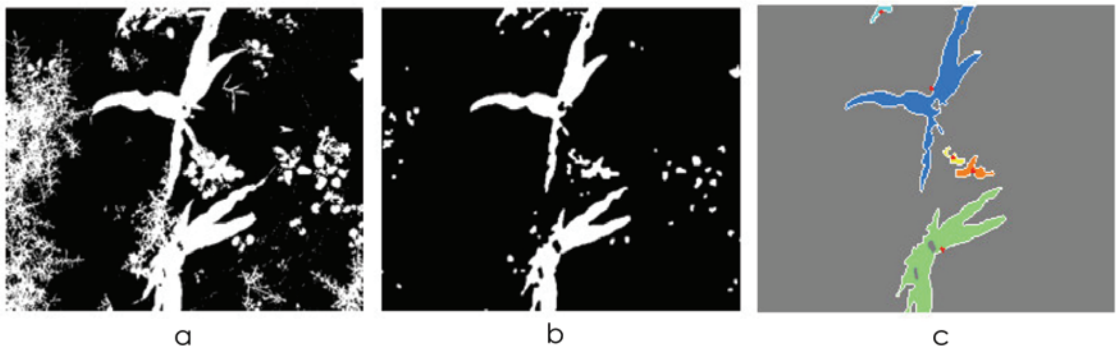

Figure 3. Object selection for shape feature extraction: (a) Binary image after soil removal; (b) Result after sequential erosion and dilation, (c) Five largest objects selected.

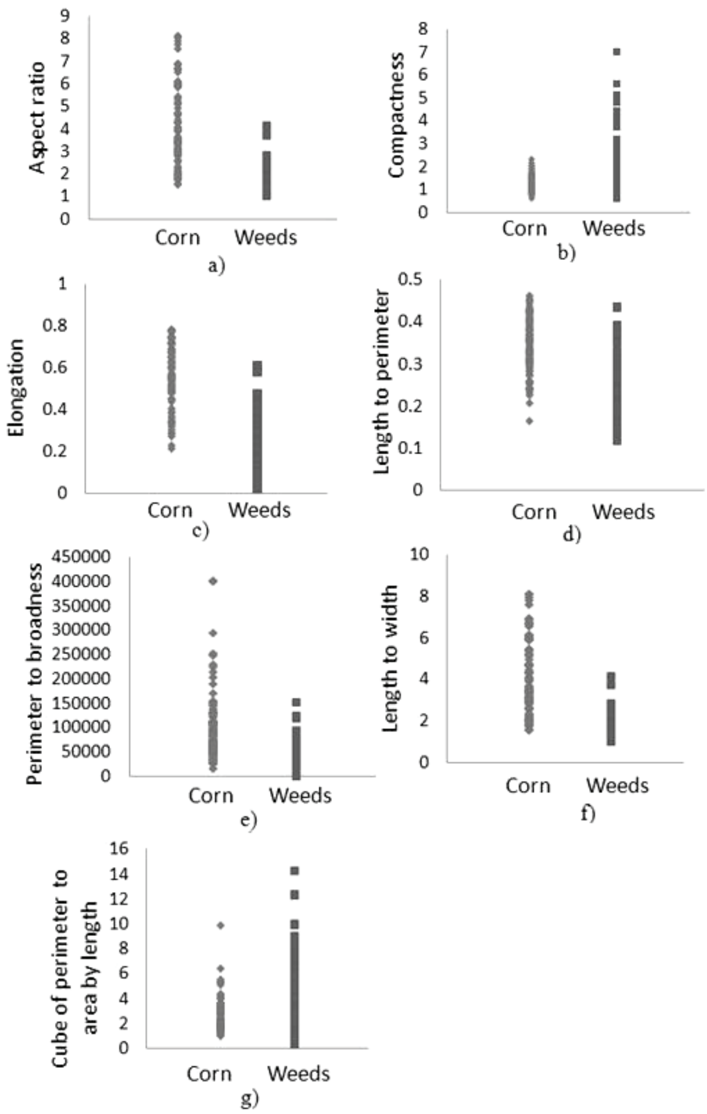

Figure 4. Values of shape features versus classification groups: (a) Aspect ratio; (b) Compactness; (c) Elongation; (d) Length to perimeter (LTP); (e) Perimeter to broadness (PTB); (f) Length to width, (g) Cube of perimeter to area by length.

classification is given in Table 2.

$$Df = -414(F_1 - 1.247(F_2) + 0835(F_3) + 2.026(F_4) \quad (2)$$

Where, Df=Discriminant function, F_1= Aspect ratio; F_2= Compactness; F_3: Perimeter to broadness, and F_4= Length to perimeter.

Plants observed in the images can now be classified by means of the discriminant function (Equation (2)) considering their distance to group's centroids. Group centroids were determined by discriminant analysis as 2.501 and -2.038 for weeds and corn groups, respectively.

The results of classification using four selected shape features are shown in Table 3. The successful recognition rate was 98.9% for corn and 95.4% for weeds (Table 3).

Classification by Artificial Neural Network

The results of discriminat analysis showed that four features of seven extracted features were sufficient to classify the plants into two groups of corn and weeds. At this stage it was intended to verify the capability of neural networks in classification as well as to verify that if there is a significant difference between the usage of four efficient features or all seven shape features. Therefore, networks were trained in two ways; using four or using the original seven features.

The results showed that the ANN model of seven inputs, one hidden layer with three nodes and two outputs was able to classify the corn and the weeds with a correct classification rate of 100% (Table 4).

To reduce the classification processing time, neural networks with four input features were investigated. Features selected by the discriminant analysis i.e. aspect ratio, compactness, perimeter to broadness and length to perimeter were used in these networks (Table 2). The results showed that the ANN classifiers having four inputs, one hidden layer with three nodes and two outputs were able to separate all the corns from the weeds in the images with 100% accuracy while 4% of the weeds were incorrectly distinguished as corn. Other networks (different nodes) were also examined as can be seen in Table 5.

Table 2. Effective shape features selected by discriminant analysis**.**

Steps	Parameter	F statistics	Wilks' lambda
1	Aspect ratio	211.821	0.478
2	Compactness	22.398	0.896
3	Perimeter to broadness	83.875	0. 698
4	Length to perimeter	141.323	0.579

Table 3. Number of observations and percentage classified correctly.

	Accuracy (%)			Number of observations		
Plant	Corn	Weeds	Total	Corn	Weeds	Total
Corn	98.9	1.1	100	87	1	88
Weeds	4.6	95.4	100	5	103	108

96.9% of original grouped cases correctly classified.

Table 4. Classification results of ANNs with different topologies and seven input features (accuracy %).

	Neural network structure					
	7-1-2		7-2-2		7-3-2	
Plant	Corn	Weeds	Corn	Weeds	Corn	Weeds
Corn	100	0	100	0	100	0
Weeds	4	96	4	96	0	100

Table 5. Classification results of ANNs with different topologies and four input features (accuracy %).

	Neural network structure					
	4-1-2		4-2-2		4-3-2	
Plant	Corn	Weeds	Corn	Weeds	Corn	Weeds
Corn	100	0	100	0	100	0
Weeds	4	96	4	96	4	96

The fewer number of input nodes, the less time is required for processing. Also fewer input features in respect to samples increases the generality of the classifier.

Based on the results acquired from networks trained with four and seven features, it can be concluded that four features are completely sufficient to distinguish the weeds from the corns. It is obvious that less feature selection would require less processing time and would enhance the final decision making for weeding machine.

Locating the Crop

In the final stage, it was intended to find the location of the crop to remove all the other plants by the mechanical weeding machine. Determining the position of the main crop is more critical for mechanical weeding comparing to patch spraying. Defining the actual crop position for the vision system is a sophisticated problem. Therefore, the centroid of the image was used as an approximation of the main stem position. Centroid of an object (p) in the binary image (bw) with a size of m×n pixels was defined by the Equations (3) and (4), while pixel values of other objects except (p) was set to zero.

$$\bar{x}_p = \frac{\sum_{i=1}^{m} i.bw(i,j)}{\sum_{i=1}^{m} bw(i,j)} \qquad (3)$$

$$\bar{y}_p = \frac{\sum_{j=1}^{n} j.bw(i,j)}{\sum_{j=1}^{n} bw(i,j)} \qquad (4)$$

Where, $\bar{x}_p$, $\bar{y}_p$ are centroid coordinates of the object *p*.

To evaluate the accuracy of using the centroid instead of the main stem of the plant, the distance between these two points was determined. Actual center of the plants was marked manually by human sight.

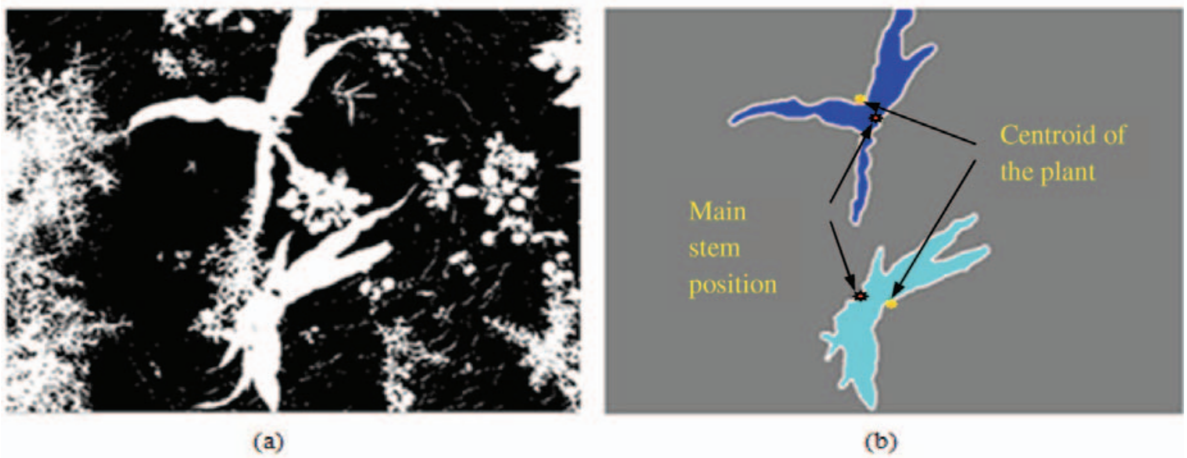

Figure 5. Locating the crop: (a) Source image and (b) Distinguished corn plants and corresponding centroids.

Figure 5 shows the final results of the source image. Forty eight images were tested and the centroids of the corns were obtained.

Locating error of the vision system was determined using the following equation which calculated the Euclidean distance between the centroid and the actual main stem position of the crop.

$$Locating\ error = \sqrt{(x_1 - x_2)^2 + (y_{1-}y_2)^2} \quad (5)$$

Where, x_1, y_1 is the real position of the stem and x_2, y_2 is the detected position of the crop by the vision system. To evaluate the performance of the system, 48 images were used and locating errors were determined. Figure 6 shows the overall system error.

CONCLUSIONS

Weed detection is the first task of autonomous weeding machines. In this study crop detection was succeeded by weed detection to govern the weeding machine to root up all the plants except the main crop. Shape features showed a good potential in discriminating the corn from the weeds. Among the seven shape features extracted from the images, four were selected by discriminant analysis which was able to classify the two groups with 98.9% accuracy. It can be concluded that three of the shape features defined for discrimination were almost parallel. Better results could be achieved when artificial neural networks were used. It was interesting that no difference was observed when four of the shape features were used instead of the original seven features and both could attain 100% correct crop detection. However 4% misclassification of weeds as corn occurred when four features were used which is not as important as the misclassification of corns as weeds. It was observed that misclassification error occurred in cases where weeds and corn leaves were partially overlaid. This caused the weed leaf to be considered as a part of the corn leaf. Therefore it can also be concluded that this method cannot be recommended to be used later than the critical period of weeding while plants have grown up.

Comparing the results achieved by discriminant analysis with that of neural networks, it is demonstrated that neural networks are more suitable for the classification of groups with overlapped features. This is due to the inherent potential of neural networks for simulating the nonlinear relations between the inputs and outputs.

It was concluded that the high recognition rate of the system is due to the considerable difference between the shape of the corn and other plants during the critical period of weeding in the location. It was also deduced from the results of neural networks that a few shape features are sufficient to differentiate the two groups. Hence, extracting more shape features would only

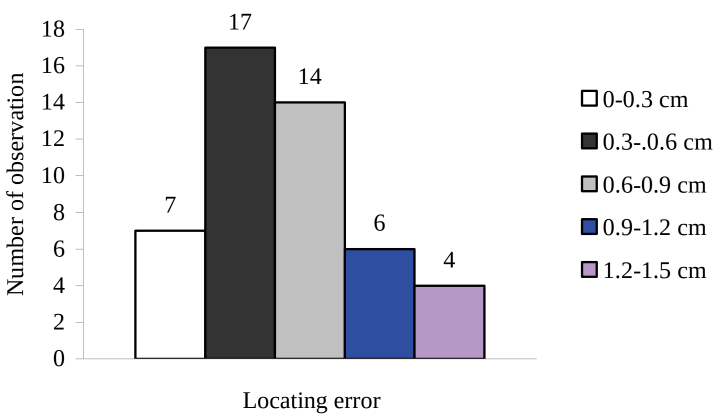

Figure 6. Crop locating error of the vision system.

increase the processing time which is not favorable for real time weeding machines. Locating the crop is the final goal of the weeding machine. Centroid of the plant image showed a good estimation of the main stem position with an error less than 1.5 cm. Such estimation seems to be reasonable for most weeding machines.

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تشخیص و مکان‌یابی محصول در مزرعه بر اساس مشخصات شکلی با استفاده از آنالیز تشخیصی و شبکه‌های عصبی مصنوعی

س. کیانی، و ع. جعفری

چکیده

توسعه و پیشرفت ماشین‌های مستقل حذف علف‌های هرز نیازمند سیستم بینایی می‌باشد که قادر به تشخیص و مکان‌یابی گیاه باشد. نکته مهم این است که سیستم بینایی می‌بایست مکان دقیق ساقه گیاه را تشخیص دهد تا از صدمه دیدن آن در حین عملیات وجین حفاظت کند. چندین ویژگی شکلی گیاه ذرت و علف‌های هرز معمول در منطقه به‌وسیله عملگرهای مورفولوژی استخراج گردید. ویژگی‌های موثر در طبقه‌بندی گیاه ذرت و علف‌های هرز توسط آنالیز تشخیصی گام به گام مورد تجزیه و تحلیل قرار گرفتند. از بین هفت ویژگی شکلی که در آنالیز تشخیصی استفاده شد، چهار ویژگی برای طبقه‌بندی دو گروه گیاه ذرت و علف‌های هرز کافی بودند. این

ویژگی‌ها به شبکه‌های عصبی مصنوعی داده شد تا علف‌های هرز را از گیاه اصلی تشخیص دهند. با استفاده از شبکه‌های عصبی مصنوعی برای جداسازی مشخصه‌های تعیین شده اقدام شد. ۱۸۰ تصویر شامل گیاه ذرت و ۴ گونه از علف‌های هرز متداول مزرعه جمع‌آوری شدند. نتایج نشان دادند که این روش قادر به تشخیص گیاه ذرت با دقت ٪۱۰۰ از علف‌های هرز می‌باشد در صورتی که ٪۴ از علف‌های هرز به عنوان ذرت شناخته شدند. در نهایت، موقعیت گیاه اصلی نیز تخمین زده شد و دقت این عمل بر اساس موقعیت واقعی گیاه، اندازه‌گیری شد. تعیین موقعیت گیاه برای ماشین وجین الزامی است تا کلیه گیاهان غیر از گیاه اصلی را ریشه کن نماید. چنین نتیجه گیری شد که دقت بالای به‌دست آمده در این روش در اثر اختلاف بارز بین گیاه ذرت و علف‌های هرز در دوره بحرانی وجین در منطقه بوده است.