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Discriminating The Corn Plants From The Weeds By Using Artificial Neural Networks

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Abstract

The main requisite for weeding-thinning machine is the location of the main stem of the crop. In this study, crops and their positions were detected using image processing techniques with the aid of artificial neural networks. Morphological operations were performed to singulate different objects in the images. Several shape features were fed to artificial neural network to discriminate between the weeds and the main crop. In the final stage, position of the crop was determined which is necessary for the weeding machine to root up all of the other plants. 196 images consisted 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 discriminate corn plants with an accuracy of 100%. It was concluded that high accuracy of this method is due to significant difference of corns and weeds in the critical period of weeding in the region.

Keywords: Crop detection, Weed, Shape analysis, image processing, ANN, thinning,

INTRODUCTION

Weed control is one of the expensive and time-consuming activities in agriculture, and long-term use of herbicide could damage people, animals and the environment. Therefore, in precision farming, it is very important to identify crops from weeds. Information on weed distribution within the field is necessary to implement spatially variable herbicide application or other implement for removing the weeds from field. Some researchers have proposed different methods for recognizing weeds in crops.

Franz *et al* (1991) used local spectral properties and shape characteristics of plant leaves to discriminate between several weed species. This study was limited to the identification of weed seedlings in growth room conditions. An automated crop spraying system developed by Brivot and Marchant (1996) tested over a range of conditions showed that up to 92% successful classification was possible using 'good' images and up to 73% with bad images. Vrindts and De Baerdemaeker (1997) showed that the discrimination between young crop plants and weeds was feasible by the analysis of spectral reflectance using specific wavelengths in the range 200–2000 nm.

S. I. Cho *et al* (2002), 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 eight shape features (aspect, roundness, compactness, elongation, perimeter to broadness, length to perimeter, length to width and cube of perimeter to area by length) were used. Aspect, elongation and perimeter to broadness were selected as significant variables for discriminate models using the STEPDISC option. Using the discriminate analysis, the successful recognition rate was 92% for radish and 98\% for weeds.

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.

Jafari *et al* (2006),The aim of their study was to extract the actual relations between three main color components R, G and B (red, green & blue), which have constituted weeds and sugar beet classes by means of discriminate analysis. They used 300 digital images of sugar beet plants and seven types of common sugar beet weeds at different normal lighting conditions to provide enough information to feed the discriminate analysis procedure. Discriminant functions and their success rate in weed detection and segmentation of different plant species have been evaluated.

In this paper a simple and practical method has been described that could easily be implemented. The main objectives were to identify shape features for detecting corn plant and to develop an algorithm for separating corn using ANN. Centroid of the plant images were considered as the plant location and its corresponding error were determined. With this method, weeder can remove all species of the weeds by means of mechanical weeding machine without using herbicides in the field. This was the first step for the development of the mechanical weeding machine that can remove all weeds in the field.

METODOLOGY

Image Acquisition

A digital camera (Canon ixus) was used to acquire digital images from several agricultural field of Fars province in Iran under various lighting conditions (from morning to afternoon). Images had a resolution of 1200 × 1600 pixels concerning to a field of view of about 50-55 cm*70-75cm on the ground and were taken at a distance of about 0.7-0.8 m from the soil surface having 24 -bit data field and JPG format. A computer Pentium IV (3.42 GHz processor) and Image Processing Toolbox version 6.2 with MATLAB version 7.7 (Math works, 2008) was used for algorithm development. The critical period for the weeding of the direct sowing corn in Fars is 25 to 30 days after the emergence. In this time, images of the corn and weeds (Amaranthus, Alhagi maurorum,Chenopodium album L,Convolvulus arvensis L) were taken in the farms of Shiraz University. In MATLAB, color images were read and processed in format RGB (red/green/blue). In RGB format, each image of M by N pixels was represented by a matrix of M by N by 3.

Soil Removal From The Image

The first stage is to classify the pixels of images according to the following classes: vegetation, soil. Studies for crop and weed detection have been performed using different spectral bands and combinations for vegetative indices. Some color vegetation indices utilize only the red, green and blue spectral bands. The advantage of using color indices is that they accentuate a particular color such as plant greenness, which should be intuitive for human comparison. In fact, two classes of plant and other things were separated by the excess green index proposed by Woebbecke *et al* (1995a) defined by the equation (1).

$$\text{Excess Green Index (EGI)}=2g-r-b \quad (1)$$

Where r, g and b were the main color components. Excess green vegetation index provides a near-binary intensity image outlining a plant region of interest. The plant regions of interest were then binarized using a selected threshold value for each set of images. Figure 1 shows sample images of corn and weeds after using excess green index and using threshold to get binary image.

Mathematical Morphology and Extracting Shape Features

The corn had oval blade shaped leaves, whereas the other common weeds had considerably different shapes. Therefore it was assumed that morphological features are able to recognize the skeleton of leaves. Morphological operations are based on arithmetic rules. Using dilation and erosion operation, components with different sizes could be segmented. As it is clearly represented in these images, the corn seedlings leaf is completely different from the weeds. So, dilate and erode operations were used to segment the corn leaves from the weeds.

The main steps were: First, the plant area was selected by using excess green vegetation index, and turned it into a black and white binary image. Secondly, a disk structure was created and continuously in three times eroded the binary image. It helped that all small objects and noises to be removed from the images. Survived objects in the images were then dilated three times to be restored to their initial extent. The third step aimed at describing unconnected objects as a function of certain geometrical features. The eight shape features (aspect ratio, roundness, compactness, elongation, perimeter to broadness, length to perimeter, length to width and cube of perimeter to area by length) were used (Tian et al., 1997; Woebbecke et al., 1995).

Artificial Neural Network

A back propagation network was used for classification which is a kind of non-linear method widely used in recognition. Fifty images of corn and 80 images of other object in the image were used to build ANN model. In the input layer, each input node was assigned to value of a shape feature. One hidden layer was used. There were two outputs in this ANN. Number of hidden nodes were changed from 1 to 3. The expected output in the training file was [1, 0] for corn, and [0, 1] for all weeds in the image. The proposed ANN model is shown in Figure.2. Log sigmoid transfer functions were applied to each processing element. Training was continued until 800 epochs had been executed. Thirty images of corns and 30 images of weeds were used to evaluate the ANN performance after training.

Results and discussion Our aim was approximately find centroid of corn that is essential for mechanical weeding

Fig.1. Binary image contains corns and weeds

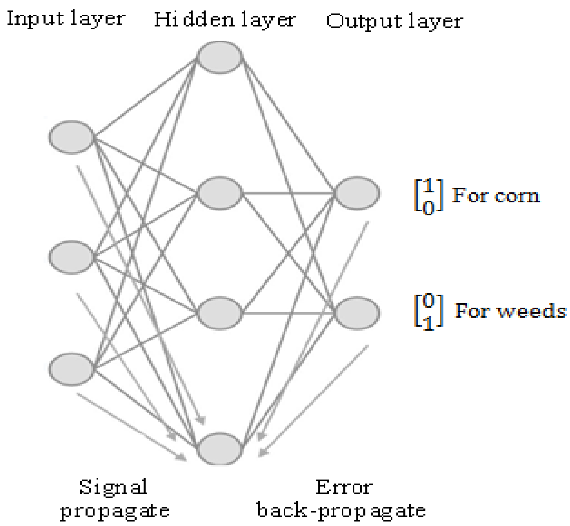

Fig.2. The structure of a neural network with back propagation

Table.1. Number of observations and percentage classified correctly (Eight shape features as ANN inputs)

ANN structure	Number of observations and accuracy (%)					
	8-1-2		8-2-2		8-3-2	
Plant	Corn	Weeds	Corn	Weeds	Corn	Weeds
Corn	100	0	100	0	100	0
Weeds	4	96	4	96	0	100

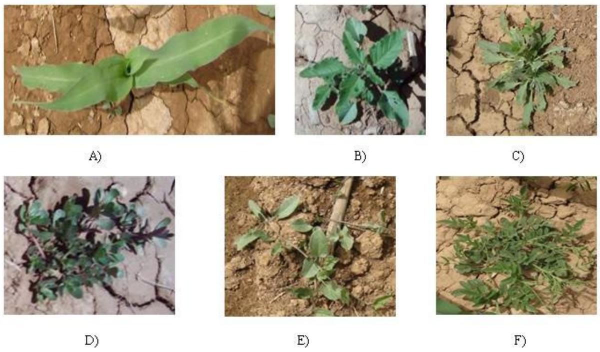

Fig.3. The binary images of the corn and some weeds; (a) Corn; (b) Amaranthus; (c) Alhagi maurorum ; (d) Convolvulus arvensis L(e) Chenopodium album L,(f) Convolvulus arvensis L

between tow crops on row. Eight shape features were extracted from the preprocessed digital images as shown in Figure.3.

By using dilation and erosion function, the weeds could be subtracted or shrink from source image. Then character attributes of the image blocks were acquired and used as features: the aspect ratio, roundness, compactness, elongation, perimeter to broadness, length to perimeter, length to width and cube of perimeter to area by length.

Locating The Crop

In as much as the weeding thinning machine have to remove all plants except the main crop, it is sufficient to define the position of the main crop (corn plants) for the machine vision system. Defining the actual crop position for the vision system is a sophisticated problem. Therefore, centroids of the plant images were considered as the main stem position and its deviation from the real center of the plant were measured. This deviation was considered as the system error in locating the plant. Forty eight images were tested and the centroids of the crons 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.

$$\text{Locating error} =[(x_1-x_2)^2+(y_1-y_2)^2]^{(1/2)} \qquad (2)$$

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 vision system. Figure 4 shows the overall system error.

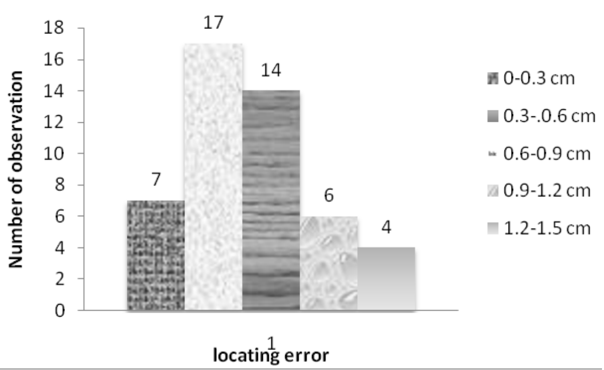

Figure 4. Crop locating error of the vision system

CONCLUSION

In precision agriculture, weed detection using image processing techniques has proved a good potential to estimate weed distribution despite the difficulties due to the similarity in spectral reflectance between weed and crop plants, and to the high variability of the natural scenes. We believe that an automatic system could be used for distinguishing crop field within common weeds. A new algorithm for the crop detection and mechanical weeding in a corn farm was developed. The eight shape features were obtained from the corn and the developed ANN model distinguished the corn from the weeds with 100% accuracy.

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