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Weeds and Corn Classification by Image Processing and Neural Network Techniques

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Abstract

Expensive and laborious job of weed control can be facilitated if automatic weeding machines are employed. Site-specific managements of the weeds in the field need accurate discrimination between the crop and the weeds. There are distinct species of the weeds so called “common weeds” for cultivation in a specific region. Three species of the weeds commonly grow in corn fields are considered in this study, which are Convolvulus arvensis, Chenopodium album, and Amaranthus retroflexus. There are distinct differences between the shapes of the plants especially in early growing stages. Therefore, ten shape features of the leaves were considered for discrimination between the weeds and corn plants. An image processing algorithm was developed and combined with the artificial neural network (ANN) for classification of corn and weeds. Several images of the leaves of each plant were taken. The ten shape features extracted from the images by image processing algorithm were fed as the input to the ANN classifier. A number of the corn and weeds leaves’ images were used to train the network. Several topologies of ANN including single and multi layer perceptrons (MLPs) with various transfer functions such as MLP-GDM, MLP-RP and MLP-SCG were used. Finally, the ability of the ANN models for classifying weeds and corn plants were evaluated using new image data. Results revealed that the ANN could discriminate corn from weeds with an accuracy of 98.5%. However, the algorithm had less accuracy for classifying the weeds from each other which was limited to 78.5%.

Keywords: Corn and weeds, Shape analysis, Artificial Neural Network, Image processing

INTRODUCTION

Weed control is one of the most important and also expensive and laborious tasks in crop production. Weeds are controlled by applying herbicides or they can be removed by mechanical instruments. Nowadays, since mechanical ways are not efficient and they are laborious, using herbicides are more common in cultivating; but most herbicides are applied uniformly although weeds are not distributed uniformly. Overusing the herbicides causes the cost of agricultural production to be increased, and also it results in dangerous damages for the environment. Based on the mentioned problems, several researches have been investigated to facilitate the cultivation operation by means of developing automatic weeding machines; furthermore, by Site-specific management of the weeds the costs of cultivation and environmental damages will be reduced. Site-specific managements of the weeds in the field need accurate discrimination between the crop and the weeds.

Several research projects have been conducted to recognize weeds in crops via employing machine vision technology. Plant shape, texture, and color [2,3,4,12] have all been investigated as possible image features for distinguishing weeds from crop plants [10].

Hayes and Han applied texture to discriminate crop and residues from soil [5]. McDonald and Chen used morphological image processing to recognize an African violet leaf from an ivy leaf [8].

Zhang and Chiasattapagon used three different approaches, color analysis, shape analysis, and texture analysis, to identify weeds (Russian thistle, redroot pigweed, Palmer amaranth, wild buckwheat, and kochia) from wheat in the field. They reported that the red and green filters could detect reddish stems of some weed species, such as redroot pigweed, kochia, and

Russian thistle effectively. Also, five shape parameters, eccentricity, compactness, and three invariant moments, were effective for shape analysis and Fourier spectrum in distinguishing based on texture [12].

Meyer et al. applied textural features to discriminate two broad leafed plants and two grasses. They reported that their algorithm was able to distinguish broad leafed plants with the accuracy of 85% and the grasses with the accuracy of 93% [9].

Jiazhi pan et al. segmented weeds and soybean seedling. They used 3CCD images in the field. They captured photos of crop and weed in fields by Multi-spectral imager, which include one crop and two weeds .Then; they segmented soil background. After that, by using morphological operations small sized weeds were deleted and the soybean image was extracted [7].

Jafari et al. 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 [6]. Discriminate functions and their success rate in weed detection and segmentation of different plant species have been evaluated [1].

This paper was devoted to develop an image processing algorithm combined with Artificial Neural Network to recognize corn and weed plants. Three species of the weeds commonly grow in corn fields were considered in this study, which are Convolvulus arvensis, Chenopodium album, and Amaranthus retroflexus. This algorithm should be capable of recognizing corn plant from weeds and distinguishing the three species of weed from each other based on some shape features extracted from leaves of each plant. This research is the preliminary stage of automatic machine to remove weeds in the field.

METHODS and MATERIALS

Image acquisition stage

In this study, it was necessary that the experimental conditions simulate the real conditions because this study was the preliminary stage of making the automatic weed controller. Therefore, for acquiring the images, a digital camera (Canon G10) was employed to capture 75 images from a corn field of Shiraz University, located in Fars province of Iran. Images had a resolution of 1200 × 1600 pixels and the images were taken in a sunny day. For grabbing the images, the camera was installed 50cm above the crop row and the images were taken perpendicularly. The images were grabbed accidently, so some images included only the image of corn and some of them included corn and weeds, which consisted of Convolvulus arvensis, Chenopodium album, and Amaranthus retroflexus (Fig 1). After that the images were prepared, they were transmitted to a computer (Pentium 4, Dual CPU, E2160 at 1.80 GHz) for image processing and further analysis.

Image processing stage

For processing the image and detect the corn from weeds and discriminating the weeds, a comprehensive algorithm designed and developed in MATLAB software (MATLAB, version 7.7, Image processing Toolbox). The first step of image processing is to segment foreground which is plants from background which is soil. This step is performed through binarizing the RGB images captured by camera and sent to the computer. Binarizing means that the captured images which have the RGB or true color space, are converted to the binary images which comprise black and white. For binarizing, the histogram of the RGB images was used. Because this study was carried out in the real condition and all the images were taken in the field, the intensity of light was not constant. In order to reduce the effects of the inconstant light, a new color space was determined according to follow:

$$r = \frac{R}{R+G+B+0.001} \quad (1)$$

$$g = \frac{G}{R^*+G^*+B^*}{}^* \qquad g = \frac{G}{R+G+B+0.001} \quad (2)$$

$$b = \frac{B}{R^*+G^*+B^*}{}^* \qquad b = \frac{B}{R+G+B+0.001} \quad (3)$$

Where R, G and B are the actual pixel values from the images based on each RGB channel. Since in each image there are some spots whose color bands have 0 value, 0.001 was added to the denominator.

Then, based on the histogram of the new color space, the threshold for converting the images into binary was determined. By applying the threshold, the plants could be segmented as a foreground from and the soil as a background in each image.

To discriminate plant from weeds and also weeds from each other, several shape properties of the leaves images of each kind of plant and weeds were extracted and considered as the input for neural network. To achieve this, 50 images were considered for training the algorithm and 25 images for evaluating the algorithm.

At the training stage, the image processing and ANN algorithm was performed according to the following steps:

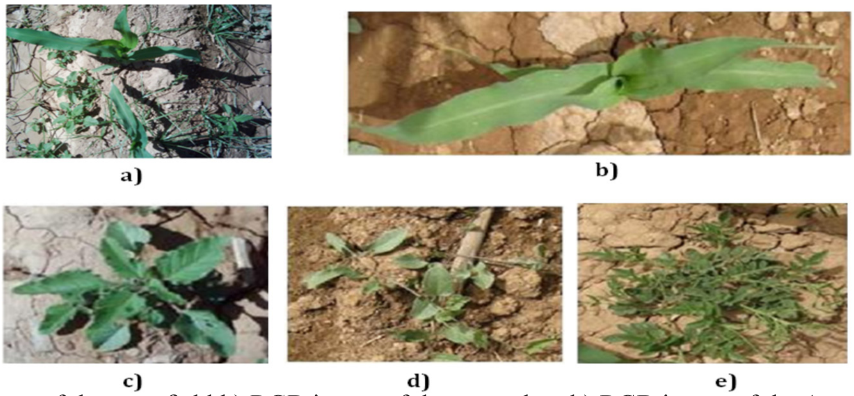

Fig 1. a) RGB image of the corn field b) RGB image of the corn plant b) RGB image of the Amaranthus retroflexus weed b) RGB image of the Chenopodium album weed b) RGB image of the Convolvulus arvensis weed

When the images were binarized and the plants were segmented from soil, each image was cropped and divided into several images manually. Therefore, in each cropped each image, there was only one group of plants. Consequently, 50 images were divided into 50 cropped images consisted of corn images, 44 cropped images comprised Amaranthus retroflexus, 37 cropped images included Chenopodium album, and 33 cropped images contained Convolvulus arvensis. Then, each cropped image were fed to the image processing algorithm for further analysis and finding morphological features of the leaves.

In this project, it was tried to develop an algorithm which was able to perform independently of the resolutions of the images in distinguishing corn from weeds. Thus, ten non-dimensional π terms were defined and employed to recognize each plant based on the shape of their leaves. The π terms did not have any dimension and so they could be used with all kind of cameras with various resolutions. The π terms were coefficient of variability (CV), leaf area to image area, aspect, roundness, compactness, elongation, perimeter to broadness, length to perimeter, and length to width and cube of perimeter to area by length.

For extracting these features from the images, the algorithm applied some functions such as erosion and dilation for each cropped and binarized image. Subsequently, unconnected objects were determined and except the biggest object, other objects were removed from the images. After that, Area, Perimeter, major axis, minor axis and centroid point of the object (image of the leaf) were established and calculated.

For determining the CV, the edge of the biggest object was detected. Then, distances between the centroid point and the edge of the object, according to the angle of each point on the edge, were measured in pixel and consequently, the CV of the distances was calculated. Also the other features were defined and calculated as follow: (some definitions are the Woebbecke et al. [11] definitions with some changes)

$$\text{Leaf area to image area} = \frac{area\ of\ object}{area\ of\ image} \quad (4)$$

$$\text{Aspect} = \frac{length\ of\ major\ axis}{length\ of\ minor\ axis} \quad (5)$$

$$\text{Roundness} = \frac{perimeter^2}{4 \times area\ of\ object \times araea\ of\ image} \quad (6)$$

$$\text{Compactness} = \frac{100 \times area\ object \times area\ of\ image}{perimeter^2} \quad (7)$$

$$\text{Elongation} = \frac{length\ of\ major\ axis - length\ of\ minor}{length\ of\ major\ axis + length\ of\ minor} \quad (8)$$

$$\text{Perimeter to broadness} = \frac{perimeter}{2(length + width)} \quad (9)$$

$$\text{Length to perimeter} = \frac{length\ of\ major\ axis}{perimeter} \quad (10)$$

$$\text{Length to width} = \frac{\text{Length}\ of\ major\ axis}{length\ of\ minor\ axis} \quad (11)$$

Cube of perimeter to area by length =

$$\frac{perimeter^2}{100\times \; area \; \phi \; object \; \times length \; \phi \; major \; axis} \tag{12}$$

Artificial Neural Network training stage

When the algorithm investigated the features and calculated them, the last step was to export the values of those 10 criteria to a series of Artificial Neural Network. In this study, several topology of ANN were used such as single and multi layer perceptrons (MLPs) with various transfer functions such as MLP-GDM, MLP-RP and MLP-SCG with various hidden layers and different numbers of neurons were evaluated and investigated to find the most accurate neural network model in detecting the plants.

Evaluation stage

After training the algorithm by 50 images, the other 25 images were employed for evaluation purposes. To evaluate the algorithm and find the most suitable ANN, like the previous stage, 25 images were imported to the algorithm. Then the algorithm segmented the plants from soil, and subsequently, each image was processed. For processing, when the algorithm defined the unconnected objects, all 10 mentioned properties were calculated and transmitted to the series of trained neural networks. Eventually, the neural networks, according to the training properties, detected the corn plant from weeds and specified the specious of each weed.

RESULTS and DISCUSSION

At the first, 75 images were grabbed from the field of corn plant. Then 50 images were used to train the neural network models according to the values of 10 shape features calculated through processing the images of the plants leaves.

After training the algorithm, for evaluating the algorithm, the comprehensive algorithm was evaluated. The purpose was to investigate whether those 10 shape criteria are useful to discriminate plant and weeds from each other and also which neural network model can provide more accurate performance. To achieve this, 25 images of corn plant and weeds were chosen. The 25 images comprised 25 images of corn, 18 images of Amaranthus retroflexus, 14 images of Chenopodium album, and 13 images of Convolvulus arvensis. The comprehensive program along with the various numbers of perceptron layers could first compute the pixel values of 10 leaf shape parameters and then detect corn leaf from weeds leaves and distinguish weeds from each. Finally, the outputs of the system's detections were compared to the detection data brought about through the vision and the percent of correct detections were calculated. Based on the calculated correct percent, the optimum number of perceptron layer and the best neural network model was defined. Table 1 reveals that Multi Layer Perceptron with RP and SCG transferring functions were more promising for detecting corn leaf from weeds leaves and also for discriminating weeds leaves from each others with the accuracy of 98.5 and 78.5, respectively. Since increasing the number of neuron in each layer causes the time of processing to be increased, the number of neurons should be optimized. The optimum neuron for both MLP-SCG and MLP-RP is 10 neuron for the input layer and 4 neurons for the hidden layer.

CONCLUSION

Site-specific managements of the weeds in the field has the ability to facilitate the weed controlling task by employing new technique such as image processing and neural network to distinguish crops and the specious of weeds, which is necessary for automating the cultivation.. Three species of the weeds commonly grow in corn fields (Convolvulus arvensis, Chenopodium album, and Amaranthus retroflexus) were considered in this study. Ten shape features of the leaves were extracted and considered for discrimination between the weeds and corn plants. An image processing algorithm combined with the artificial neural network (ANN) was developed and for classification of corn and weeds. Several images of the leaves of each plant were taken. Several topologies of ANN including single and multi layer perceptrons (MLPs) with various transfer functions such as MLP-GDM, MLP-RP and MLP-SCG were used. Results showed that the ANN could discriminate corn from weeds with an accuracy of 98.5%. However, the algorithm had less accuracy for classifying the weeds from each other which was limited to 78.5%. Therefore, the algorithm is capable of being used in automatic weed controller machine in the field.

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Table 1. Artificial neural network models and percentage of accuracy in discriminating

ANN model	Input Layer	Hidden Layer	%correct for detecting corn from weeds	%correct for discriminating weeds from each other
Single Layer Perceptron-P Learning	-	-	38.57	15.56
Single Layer Perceptron-PN learning	-	-	48.57	20.00
MLP-GDM	10	2	78.57	40.00
	10	3	67.14	46.67
	10	4	77.14	42.22
	10	5	70.00	51.11
MLP-SCG	10	2	52.86	62.22
	10	3	87.14	78.78*
	10	4	98.57 *	78.78 *
	10	5	98.57 *	78.78 *
MLP-RP	10	2	85.71	46.67
	10	3	87.14	62.22
	10	4	98.57 *	78.78 *
	10	5	98.57 *	78.78 *

*indicates the minimum error in classification

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