WEED DETECTION BY MACHINE VISION AND ARTIFICIAL NEURAL NETWORK

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ABSTRACT

A machine vision system using charge coupled device(CCD) camera for the weed detection in a radish farm was developed. Shape features were analyzed with the binary images obtained from color images of radish and weeds. Aspect, Elongation and PTB were selected as significant variables for discriminant models using the STEPDISC option. The selected variables were used in the DISCRIM procedure to compute a discriminant function for classifying images into one of the two classes. Using discriminant analysis, the successful recognition rate was 92% for radish and 98% for weeds.

To recognize radish and weeds more effectively than the discriminant analysis, an artificial neural network(ANN) was used. The developed ANN model distinguished the radish from the weeds with 100%. The performance of ANNs was improved to prevent overfitting and to generalize well using a regularization method. The successful recognition rate in the farms was 93.3% for radish and 93.8% for weeds.

As a whole, the machine vision system using CCD camera with the artificial neural network was useful to detect weeds in the radish farms.

Keywords: Precision farming, Weed, Machine vision, Pattern recognition, Discriminant analysis, Artificial neural network

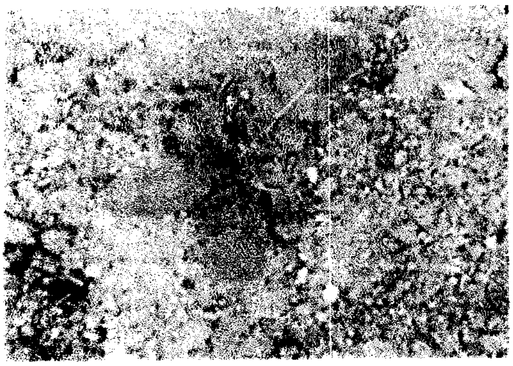
INTRODUCTION

Weed control is one of the expensive and time-consuming activities in agriculture. And long-term use of herbicide could damage human, animals and the environment. Agricultural herbicides have been uniformly sprayed in a field and overused in a conventional way. This had made severe environmental pollution. Therefore, weed-detecting technologies for precision spraying using selective herbicides need to be developed for saving herbicides and reducing the environmental pollution. Site specific crop management(SSCM) can reduce the usage of agricultural herbicides from 40% to 80% with maintaining effect of herbicides.(Heisel *et al.*, 1997). Several researchers have been conducted for weed detection using image processing (Benlloch *et al.*, 1997; Tian *et al.*, 1997; Woebbecke *et al.*, 1995). Shape features of wheat, corn and soybean were extracted and discriminant analysis was applied for identifying weeds (Meyer *et al.*, 1998; Zhang *et al.*, 1995). Recently, artificial neural network(ANN) was widely used for improving conventional modeling techniques.

The main objective was to identify shape features for detecting weeds commonly found in radish farms and to develop an algorithm for separating weeds using the ANN. According to our survey, about 90% weeds are found unoverlapped with the radish plants. Therefore, the weeds overlapped with the radish were not handled in this research.

MATERIALS AND METHODS

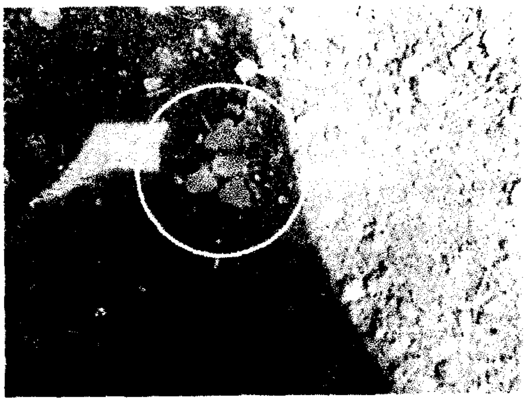
The CCD color images were taken for this study from two radish farms in the spring of 1999. Radish plants from three leaves to five leaves stage were observed (figure 1-a). The weeds were selected for this study by dominant index in Korean radish farms : purslane(*Portuloca oleracea L.*), crabgrass(*Digitaria sanguinalis Scop.*), and goosefoot(*Chenopodium album var.*). These weed species (figure 1-b, c, d) were used as the objects to be separated from the radish.



(a) radish

(b) purslane

(d) crabgrass



(d) goosefoot

Fig. 1 Color images of various weeds and radish

Acquiring Images and Extracting Shape Features

The radishes were planted on May 18 1999, and the color images were taken on June 8 and 9. A device with a RGB CCD camera(JVC, TK-1070U) and light sources was used to take color images of the radishes and the weeds(figures 2 and 3). There were 50 images of radishes, 50 images of purslanes, 40 images of crabgrasses, and 10 images of goosefoots. Initial image process was performed on the images using the Photoshop(Adobe system, USA) to classify the radish and the weeds from soil. The preprocessed images were imported into the Image-Pro Plus(Media Cybernetics, USA) for shape analysis. The 8 shape features were used and defined in table 1.

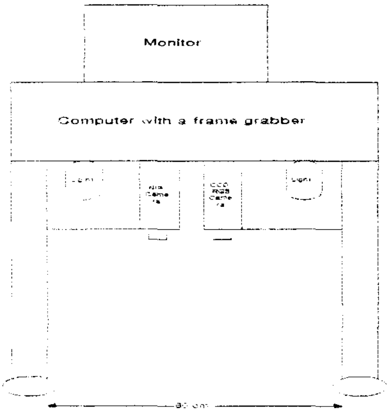


Fig. 2 Vision system architecture for the field experiment

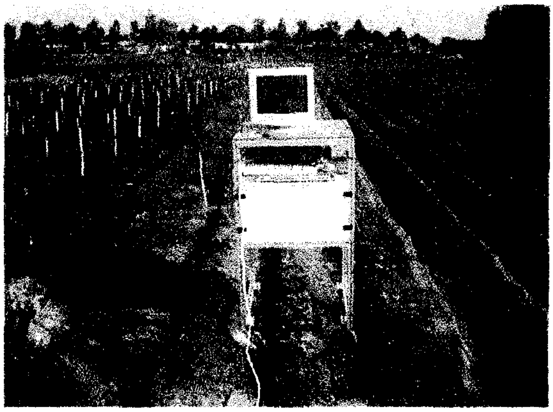


Fig. 3 Mobile platform with vision system

Table 1. The definitions of shape features

Shape Features	Definition
Aspect	$\frac{\text{length of major axis}}{\text{length of minor axis}}$
Roundness	$\frac{\text{perimeter}^2}{4\times\pi\times\text{area}}$
Compactness	$\frac{100\times\text{area}}{\text{perimeter}^2}$
Elongation	$\frac{\text{length of major axis - length of minor axis}}{\text{length of major axis + length of minor axis}}$
PTB	$\frac{\text{perimeter}}{2(\text{length+ width})}$
LTP	length
LTW	length
PTAL	perimeter^3

Discriminant Analysis.

Discriminant analysis techniques were used to classify individual object into one of two groups: "radish" or "weed". SAS(SAS Institute Inc., USA) provided the DISCRIM and the STEPDISC procedures. The stepwise option of the STEPDISC package was first used to select significant variables for discriminant models based on their classification power. Model variables chosen using the STEPDISC option were then used in the DISCRIM procedure to compute a discriminant function for classifying observations into one of the two classes.

Artificial Neural Network(ANN)

Back propagation networks were used for an artificial neural network modeling. 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. The expected output in the training file was [1,0] for radish, and [0,1] for weeds. The proposed ANN model was shown in figure 4. Log sigmoid transfer functions were applied to each PE(processing element). Training was continued until 50000 epochs had been executed. 10 images of radishes and 20 images of weeds were used to evaluate the ANN performance after training.

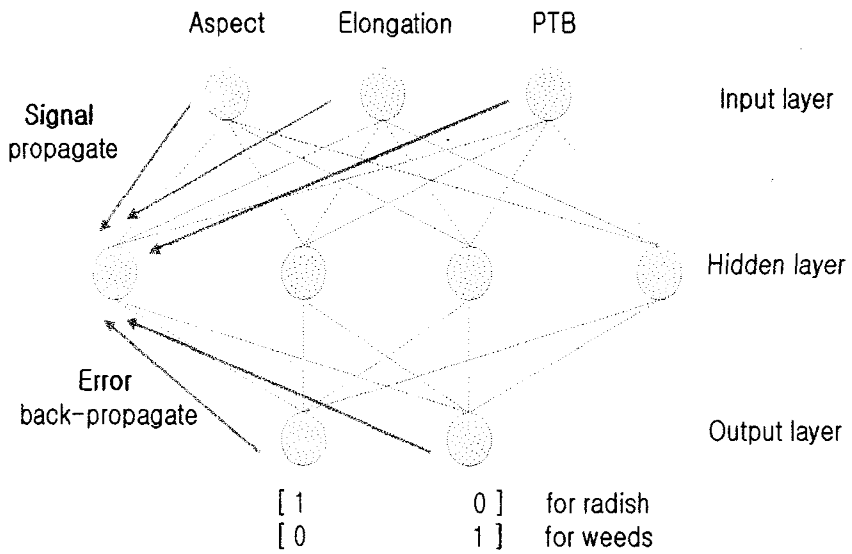


Fig. 4 The structure of neural network with back-propagation

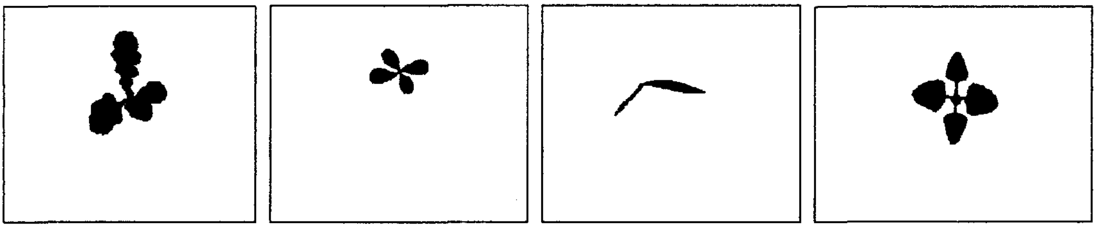
Improved Artificial Neural Network(ANN)

To improve the ANN model, a regularization method using a modified performance function was applied. It was possible to improve generalization if the performance function was modified by adding a term that consisted of the mean of the sum of squares of the network weights and biases. This made the network have smaller weights and biases and forced the network response to be smoother and less overfitted.

RESULTS AND DISCUSSIONS

Extraction of Shape Features

The 8 shape features were extracted from the binary digital images as shown in figure 5. The mean values of the obtained shape features were displayed in figure 6.



(a) radish (b) purslane (c) crabgrass (d) goosefoot

Fig. 5 The binary images

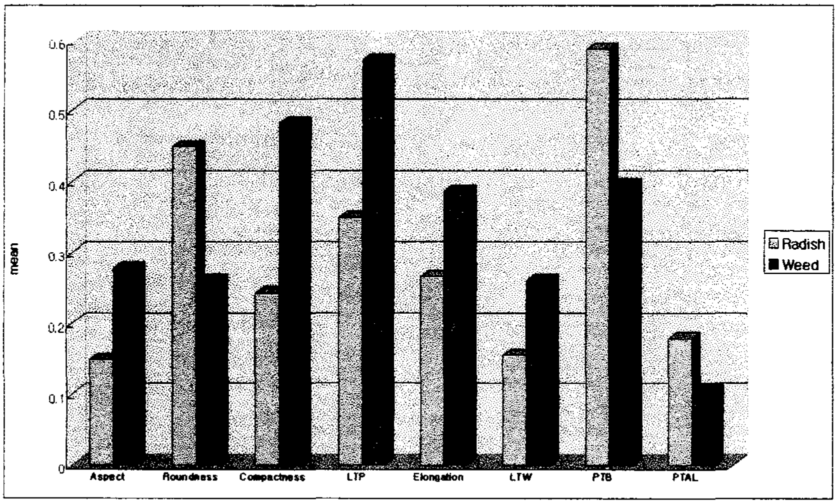


Fig. 6 Mean values of the shape features

Classification by Discriminant Analysis

For the discriminant analysis, three shape features were chosen by a stepwise selection method as shown in table 3. The result was shown in table 4. Using the discriminant analysis, the successful recognition rate was 92% for radish and 98% for weeds.

Table 3. Stepwise selection

STEP	Parameter	Partial-R^2	F statistics	Probability > F	Wilk's Lambda	Average Squared Canonical Correlation
1	PTB	0.6926	333.441	0.0001	0.30741020	0.68258980
2	ELONG	0.0774	12.341	0.0006	0.28360129	0.71639871
3	ASPECT	0.0351	5.310	0.0226	0.27364840	0.72635160

Table 4. Number of observations and percent classified into type

TYPE		Radish	Weed	Total
Radish	Hit numbers	46	4	50
	(percent)	92.0%	8.0%	100%
Weed	Hit numbers	2	98	100
	(percent)	2.0%	98.0%	100%

Classification by ANN Model

ANN models were developed using the three shape features selected by the discriminant analysis and the original 8 features(table 5). The developed 8-7-2 ANN model using the 8 features distinguished the radish from the weeds with 100% and compared with the other models (table 6).

Table 5. Hit numbers as the numbers of hidden nodes

(a) Hit numbers using 3 shape features as ANN inputs

Number of hidden nodes	2	3	4	5	6	7	8	9	10
Radish	10	9	10	10	9	9	9	9	9
Weed	19	19	19	19	19	19	19	19	19

(b) Hit numbers using 8 shape features as ANN inputs

Number of hidden nodes	2	3	4	5	6	7	8	9	10
Radish	10	9	7	10	10	10	9	7	9
Weed	19	19	18	19	18	20	18	17	19

Table 6. Number of observations and percent classified correctly.

From \ To	3-2-2		3-4-2		8-7-2	
	R	W	R	W	R	W
R	100.00% (10)	0.00% (0)	100.0% (10)	0.00% (0)	100.0% (10)	0.00% (0)
W	5.00% (1)	95.0% (19)	5.00% (1)	95.0% (19)	0.00% (0)	100.0% (30)

* R : radish, W : the others (crabgrass, purslane, goosefoot)

Classification by the improved ANN model

Performance of the ANN models was improved to recognize the radish and the four weeds more effectively using the regularization method. The results were shown in table 7. Even the ANN models having two and seven hidden layers with the three shape features separated all the weeds from the radish image.

Table 7. Hit numbers in the improved neural network

(a) Hit numbers using 3 shape features as ANN inputs

Number of hidden nodes	2	3	4	5	6	7	8	9	10
Radish	10	10	10	10	10	10	10	10	10
Weed	20	19	19	19	19	20	19	19	19

(b) Hit numbers using 8 shape features as ANN inputs

Number of hidden nodes	2	3	4	5	6	7	8	9	10

Radish	10	10	7	10	10	8	7	7	8
Weed	20	20	18	20	19	19	19	19	18

CONCLUSIONS

The eight shape features were obtained from the radish and weeds. Using the discriminant analysis, the successful recognition rate was 92% for the radish and 98% for the weeds. The developed ANN model distinguished the radish from the weeds by 100%. The performance of ANN models was improved to recognize the radish and the weeds more effectively in simple ANN structure using a regularization method. The machine vision system utilizing ANN model was feasible to detect the weeds. However, further studies should be taken on the weeds partially hidden by the crop plants.

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