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Full Length Research Paper

Identification of weed/corn using BP network based on wavelet features and fractal dimension

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The aim of this study was to investigate weed/corn Back-propagation (BP) network discrimination method based on wavelet feature parameters and fractal dimension of young weed/corn image. In-filed images were taken under natural sunlight and various backgrounds, and five common weed species located corns fields were considered in this research. The obtained images were converted into gray level images on a black background by a color index (ExG – ExR). Energy values were calculated from wavelet coefficients by using two-level wavelet decomposed gray level images. Then the obtained seven energy parameters were used as input vector to construct BP network classifier. The results showed that monocotyledon and dicotyledon could be totally separated with 100% accuracy, whereas weed/corn could not be effectively separated. To improve identification accuracy, the fractal dimension of weed/corn image was added to the original input vector. The results of this experiment demonstrated that BP network classifier associated with seven wavelet energy parameters provided 77.14% recognition rate (correctly identify weeds and corns), whereas BP network classifier associated determined by wavelet energy parameters and fractal dimension achieved a better recognition rate 94.28%.

Key words: Corn seedling, weeds, wavelet transform, energy, fractal dimension, identify.

INTRODUCTION

Weed species retard the growth of the crop and reduce farm yields. To control or even kill weed species, a large number of herbicides or chemicals are used in agricultural fields, which results in drinking water and environmental pollution. Currently, it therefore is essential to successfully identify the weeds from the crop to selectively spray herbicides or chemicals to reduce chemical waste and protect drinking water and environmental safety. Some previous researches have been done to apply machine vision to detect or recognize weeds in order to solve this problem (Aitkenhead et al., 2003; Grundy et al., 2005; Wang et al., 2007; Bacchetta et al., 2008). However, most of the work had been done with an indoor condition or controlled illumination, not taking into account natural sunlight and complicated field backgrounds.

It is necessary that the identification algorithm be capable of categorizing images with considerably high accuracy. Efficient feature extraction is the most important step in classifying the object. Some work was mainly based on statistical analysis of shape, color and texture features (Pe´reza et al., 2000; Kavdir, 2004; Burks et al., 2005). Manh et al. (2001) used deformable templates to segment weed leaf. Other methods have used the alignment of crop rows to identify inter-row weeds (Olsen, 1995; Marchant, 1996; SØgaard and Olsen, 2003), or have focused on multispectral images analysis (Feyaerts and Gool, 2001; Jurado-Exposito et al., 2003).

Once the features have been extracted from the interest object, the next step is to identify or classify them. Statistical method (Tellaeche et al., 2008) and Artificial Neural Networks (ANNs) are commonly used for object classification. Especially, ANNs which can efficiently model various input/output relationships were often employed in classification of plants. Burks et al. (2005) studied and evaluated three neural network models (counter propagation, back propagation, and radial basis function) using texture features to classify 5 weed species and clear soil surface. The results showed

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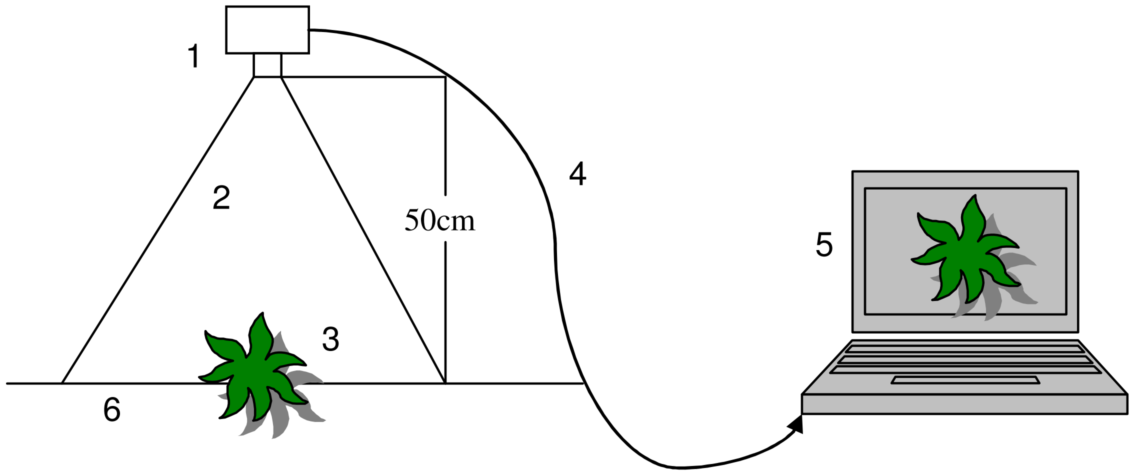

Figure 1. Illustration of the experimental setup: (1) Camera; (2) Tripod; (3) Plant; (4) Data line; (5) computer for image acquisition; (6) Soil.

that back propagation network classifier provided the highest accuracy of 97%, which exceeded others.

This study mainly focused on weed/corn recognition problems in various field backgrounds. A color index with the global threshold was used to segment the objective embedded in these backgrounds and then wavelet-based feature parameters and fractal dimension were used to construct BP network classifier.

MATERIALS AND METHODS

Camera system and image samples

A digital camera was used to acquire weed/corn color images at early stage of corn growth. The camera was mounted on the top of the tripod when the images were taken. The vertical distance from the camera to the ground was 50 cm (Figure 1) (El-Faki et al., 2000).

The original images were taken randomly from the experimental fields of Huazhong Agricultural University in China in May 2006. For the purpose of experiment, all these images were captured with a 640 × 480 pixels resolution under different natural sunlight and field background conditions. These conditions included different weather conditions (cloudy or sunny) and the bare soil and residues backgrounds (corn stalk, dead plant material and others). One or more the sub-images (256 × 256 pixels) containing one plant, either the weed or the corn seedling, were extracted from each obtained original image, stored as 24 bit color images and saved in RGB color space in the BMP file format. These sub-images would be used as image samples to extract feature parameters.

Some typical weed/corn image samples were shown in Figure 2, in which weed species, including monocotyledon (Goose grass and Rice Galingale) and dicotyledon (Yerbadetajo, Common Carpesium and Copperleaf), were commonly found from corn fields in China. The samples were taken as two cases in the following classifier: the corn and the weed.

Image processing

The initial goal in the present weed detection task was to divide the different pixels of the image into two classes: background and plant. This processing was called the image segmentation which could be completed by converting RGB images into gray level images. Various methods were proposed to segment RGB images. Hemming and Rath (2001) used HIS space to transform the original images. Pe´reza et al. (2000) used the NDI (normalized difference index) to transform the images to solve light problems. Some recent researchers used excess green (ExG) index to convert the original images into gray level images (SØgaard and Olsen, 2003; Sena-Jr et al., 2003; Ishak et al., 2009; and others). Meyer and Camargo-Neto (2008) tested the ExG, NDI, and ExG – ExR (ExR denotes excess red index) which was denoted by ExG – ExR for separating plant from different backgrounds. In his research, the ExG – ExR index would be used, here

$$\begin{aligned} ExG &= 2 \times green - red - blue \\ ExR &= 1.4 \times red - green \end{aligned} \tag{1}$$

where red, $green$ and $blue$ is the intensity values in the red, green, blue channels of a pixel, respectively, and ExG, ExR are the intensity values of the output grey level images.

One of advantages of ExG – ExR index was that the obtained gray level images had unique background that is, the values of the pixels of the background were 0, this enable one to easily separate object from background. The gray level images corresponding to Figure 2 were shown in Figure 3.

Next, a main task was to find weed/corn feature parameters and develop effective weed/corn recognition algorithm. Differing from the existing researches, in this research wavelet-based feature parameters and fractal dimension were used to set up BP network classifiers.

Wavelet feature extraction

For BP network recognition method, its classification effect is closely related to the feature extraction of the recognized objects. In this article, wavelet transform was used to extract the features of weed/corn images.

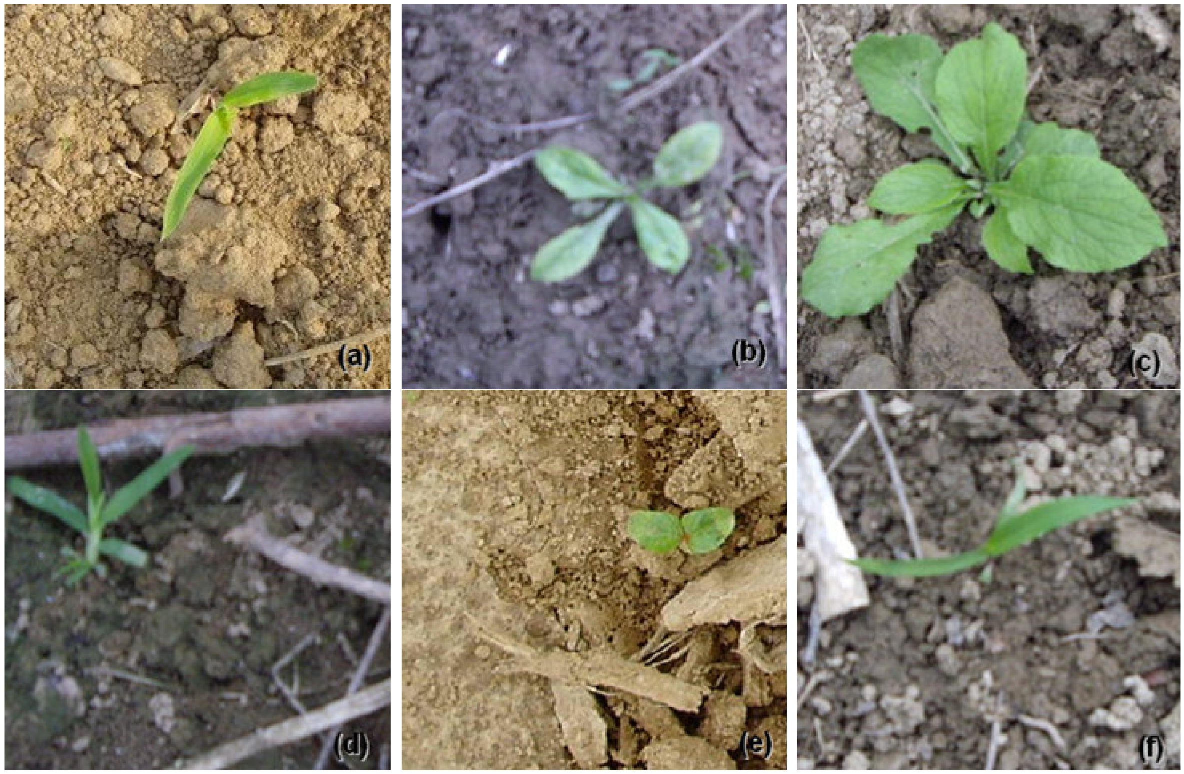

Figure 2. Image samples (256×256 pixels): (a) Corn seedling, (b) Yerbadetajo, (c) Common Carpesium, (d) Goose grass, (e) Copperleaf, (f) Rice Galingale.

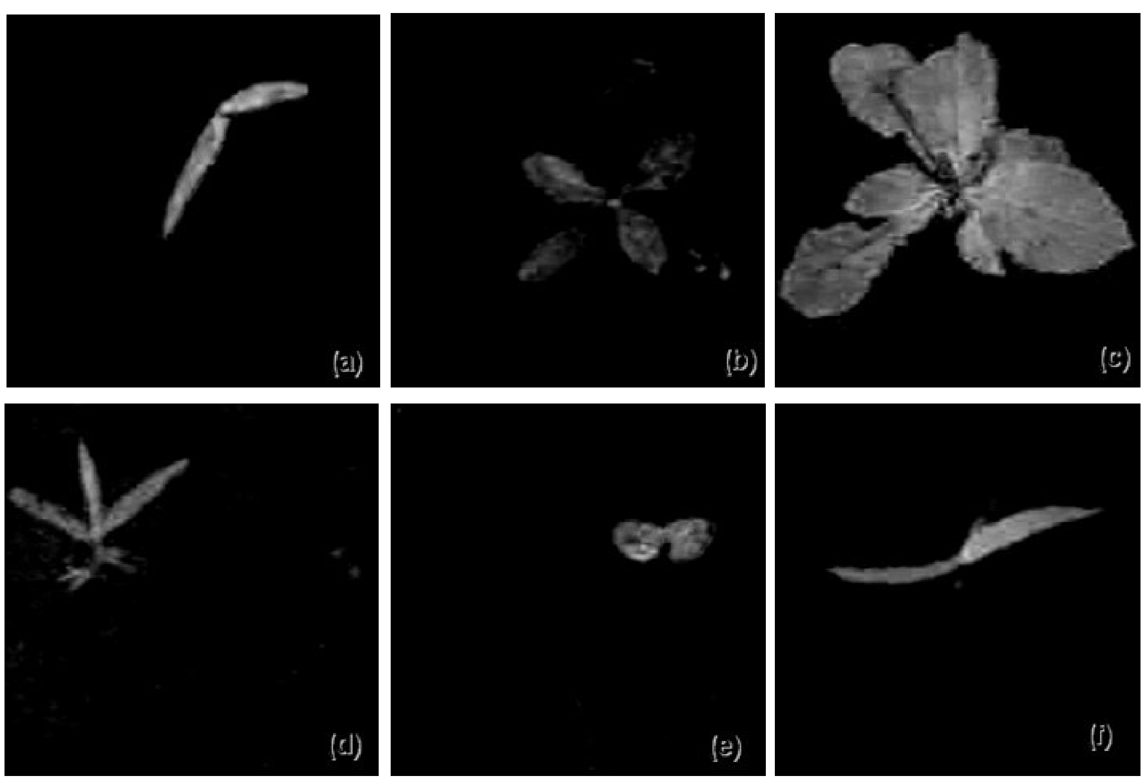

Figure 3. Gray level images: (a) Corn seedling;(b) Yerbadetajo; (c) Common carpesium; (d) Goose grass; (e) Copperleaf; (f) Rice galingale.

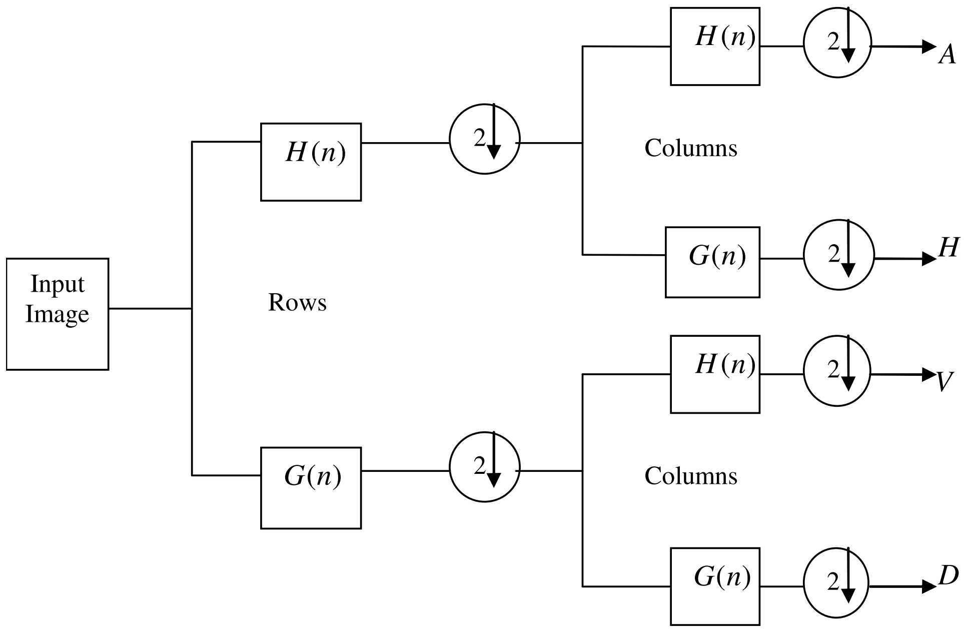

Figure 4. Wavelet decomposition using a filter band.

Considered a family of wavelet $\psi_{a,b}(t) = a^{-\frac{1}{2}}\psi(\frac{t-b}{a})$, $b \in R, a \in R^{+}$, a family of discrete wavelet can be obtained by scaling and translating with the parameters $a = a_0^{\ j}, b = ka_0^{\ -j}b_0$, the formula as follows:

$$\psi_{j,k}(t) = a_0^{-0.5j}\psi(a_0^{\ -j}t - kb_0) \quad j,k \in Z \tag{2}$$

where $a_0 > 0$, $a_0 \neq 1$, $b_0 \in R$. In the application, the common wavelet coefficients are $a_0 = 2$ and $b_0 = 1$. In order to obtain discrete wavelet coefficients of an image, a combination of high and low-pass wavelet filter was used (Gonzalez et al., 2004, Figure 4).

In 2D analysis, an image was decomposed into coarser resolutions using a simple hierarchical scheme (see Figure 4). The input original image was decomposed by the rows at first with a low-pass filter $H(n)$ and high-pass filter $G(n)$. The resulting image was down-sampled by a factor of 2. Subsequently, each of the outputs was again convoluted by the columns. Hence, the coefficient of the lower resolution image, that is, A, and three coefficients of the detail images, H, V, D were acquired. In this paper two-level wavelet transform was used, and the schematic diagram of wavelet composition was shown in Figure 5.

Thus for a given weed/corn image, the two-level wavelet transform generates the approximation components A2 and detail components H1, V1, D1, H2, V2, D2. One of the most popular and efficient wavelet features is the energy of wavelet-decomposed images (Choudhary et al., 2008). In this paper, the energy of each component of two-level wavelet composition was viewed as a feature parameter of weed/corn image, which was calculated by the following formulation

<table>
<tr><td>A2</td><td>H2</td><td rowspan="2">H1</td></tr>
<tr><td>V2</td><td>D2</td></tr>
<tr><td colspan="2">V1</td><td>D1</td></tr>
</table>

Figure 5. Schematic diagram of two-level wavelet composition.

$$E = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(s(i,j))^2 \tag{3}$$

where $s(i,j)$ is the wavelet transform coefficient at the point (i,j) for any component of size $N \times M$. Since the energy values of components obtained from decomposed images ranged largely, the normalization energy values would be used to develop our recognition method, which were defined as follows:

$$\begin{aligned} e_J &= \frac{E_J}{E_{A2} + E_{H2} + E_{V2} + E_{D2}}, J = A2 \\ e_{Ji} &= \frac{E_{Ji}}{E_{Ai}}, J = H, V, D, i = 1,2 \end{aligned} \tag{4}$$

Where E_J is the energy of component J which can be obtained from formulation (3).

To this end, we could gain seven wavelet-based features from Eq. (4) for a given weed/corn image sample. As an example, the wavelet-based feature values of image samples shown in Figure 3 were listed in Table 1. Note that Daubechies wavelet family is the most popular mother wavelet family for image texture analysis due to their compact support and orthogonality (choudhary et al., 2008). In this research DB1 wavelet was employed.

Table 1. Wavelet-based feature values of image samples in Figure 3.

Type	e_{A2}	e_{H1}	e_{V1}	e_{D1}	e_{H2}	e_{V2}	e_{D2}
(a)	0.983	0.005	0.006	0.0029	0.0071	0.008	0.0022
(b)	0.9881	0.0018	0.0023	0.0003	0.0071	0.0042	0.0008
(c)	0.9785	0.0031	0.0039	0.0003	0.0128	0.0076	0.0011
(d)	0.9747	0.0097	0.0052	0.0011	0.0141	0.0107	0.0012
(e)	0.9853	0.0054	0.0041	0.0009	0.0078	0.0054	0.0017
(F)	0.9819	0.0074	0.0032	0.0007	0.0116	0.006	0.0009

Fractal dimension

Fractal dimension is an interesting parameter to characterize roughness in an image. It can be used in texture segmentation, estimation of three-dimensional (3D) shape and other information (Sarkar and Chaudhuri, 1992). Naturally, the fractal dimension can be expected to be a good feature parameter for weed/corn images. One of the most widely used algorithms which compute fractal dimension is box-counting method. The box-counting method is based on the number of boxes $N(\delta)$ of size δ required to fill the entire area of an image. The box-counting method defines the fractal dimension of an object by the expression (Bruno et al., 2008):

$$d \sim \log N(\delta) / \log \delta \quad (5)$$

In this study, a global threshold with 0 was used to binarize the gray level images. Hence, fractal dimension was calculated from the obtained binary images.

BP classifier

Back-propagation (BP) networks were selected for this study which had been successfully used for various image recognition problems in agriculture (Paliwal et al., 2003; Kavdir, 2004). BP network in this work consisted of one input layer, one hidden layer and one output layer. The number of nodes in input layer was the number of feature parameters obtained from wavelet-decomposed and fractal dimension. There were two outputs in the BP classifier. The expect output was [1, 0] for the corn, and [0, 1] for the weed. One hidden layer was used between the input layer and output layer. Number of the nodes in the hidden layer was calculated by (Visen et al., 2002).

$$n = (\frac{n_i + n_o}{2}) + y^{0.5} \quad (6)$$

where n_i is the number of input nodes, n_o is the number of output nodes and y is the number of input samples in the training set. In this study, to acquire better accuracy, n was improved by adding η ($\eta = 0,1,2$).

Logistic sigmoid transfer functions were applied to each processing element. Training was continued until 10,000 epochs had been executed. BP network was trained and the weights were adjusted according to the error between the target output and the actual output unit the mean square error to 0.05 or the maximum number of epochs was reached.

Classification rule

The success classification rates were given by the following formula.

$$\text{Recognition rate} = \frac{TC + TW}{S} \times 100\% \quad (7)$$

where TC denotes the correct identified corns, TW the correct identified weeds, and S the sum of the samples.

RESULTS AND DISCUSSION

The image samples used in our experiment were consisted of 35 corn and 49 weed images. Training of the BP network was carried out by 49 out of 84 images (20 corn and 29 weed images). The performance of the BP network was tested using the rest image sample (15 corn and 20 weed images). The number of neurons in input layer varied according to the selected feature parameters. Input variables in this study were energy value (7), fractal dimension (1) and energy value + fractal dimension (8), respectively.

The recognition results of BP classifier with 7-12-2 configuration based on seven wavelet-based feature parameters showed that 9 images were classified into the corn and 18 into the weed. The correct recognition rate was 77.14%, as shown in Table 2. Through further trial and analysis, we found that misleading 2 weeds were totally monocotyledon. Hence, the further experiment between monocotyledon and dicotyledon using energy coefficients was done. The result had been shown in Table 3.

As shown in Table 2, the training and testing best accuracy using energy parameters as input variables of BP classifier were 81.63% and 77.14%, respectively. Neuron configuration of the BP network was 7-12-2. Using fractal dimension as input variable, the number of neurons in hidden layer was 8, 9, and 10 in order to acquire better accuracy. The best accuracy in the trial

Table 2. Classification rate of training dataset and testing dataset using different input parameters.

Feature Parameter	No. nodes in the hidden layer[1]	Classification rate[2] (%)	
		Training dataset	Testing dataset
Energy	11	77.55	71.43
	12	81.63	77.14
	13	81.63	74.29
Fractal dimension	8	79.59	71.43
	9	85.71	80.00
	10	83.67	74.28
All[3]	12	89.79	88.57
	13	93.87	91.43
	14	97.95	94.28

[1]Numbers of the hidden layer obtained using Eq. (6) add η

[2]Classification rate is calculated by Eq. (7).

[3]All represent the parameters combining energy with fractal dimension.

Table 3. Comparison of monocotyledon and dicotyledon by energy features.

Type	Monocotyledon	Dicotyledon
Monocotyledon[1]	51	0
Dicotyledon	0	33

[1]Monocotyledon includes the corns and weeds.

was 80%, which was obtained from a BP network with 1-9-2 neuron configuration. Combining energy values with fractal dimension as input parameters, the best testing accuracy was improved to 94.28%, which was obtained from the BP network classifier with 8-14-2 neuron configuration.

In this research, dicotyledon such as Yerbadetajo, Common Carpesium and Copperleaf were commonly found in the corn field. Monocotyledon included the corns and the weeds (Rice Galingale and Goose grass). Because energy distribution can represent the texture features of objects, monocotyledon could be separated from the dicotyledon using energy parameters as input vectors. As shown in Table 3, 51 monocotyledon images were classified into monocotyledon and 0 into dicotyledon, while 33 dicotyledon images were identified as dicotyledon and 0 as monocotyledon. This experiment provided accuracy as high as 100% in discriminating between dicotyledon and monocotyledon.

Conclusion

Identification weed/corn in field conditions at the early growth stage based on discrete wavelet transform and fractal dimension for feature extraction and classification using a back-propagation network has been developed and evaluated. From this research, the following findings can be concluded.

(1) Using ExG – ExR index, color vegetation can be separate from the various field backgrounds, and the corresponding gray level images with a uniform background are acquired.
(2) The energy features are extracted by multi-resolution analysis from obtained gray level images. The experimental results show that energy features can more effectively separate monocotyledon from dicotyledon with 100% accuracy. The best weed/corn recognition rate, however, is only 77.14%.
(3) Fractal dimension as input vector of BP classifier is calculated from binary images. The best classification accuracy with fractal dimension as input vector is 80%.
(4) The back-propagation algorithm is used to train and test the network. It is shown that the model combining energy parameters and fractal dimension features can be used successfully to identify the weed from the young corns. The result obtained demonstrated that the proposed features can be used to classify weed/corn with overall accuracy rate of 94.28%.

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