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Full Length Research Paper

Weed/corn seedling recognition by support vector machine using texture features

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This study investigated the effect of a new approach, the support vector machine, as a classifier tool to identify the weeds in corn fields at early growth stage. Image segmentation was done by transforming original color images to gray level images according to the statistical values of red, green, blue components. The Gray Level Co-occurrence Matrix (GLCM) and statistical properties of the histogram from the gray level images were further used to obtain the texture features of the weeds and corn seedlings. These texture features were used in the classification procedure. Principle component analysis was used to select the texture features according to their better contributions to reduce space dimensions. A Support Vector Machine (SVM) classifier was employed to recognize the weeds and the corn seedlings. The results indicated that the SVM classifiers with different feature selections could identify successfully weed-corn with a higher accuracy ranged from 92.31 to 100%. A comparison study of the recognition capabilities of SVM and back-propagation (BP) neural-network classifier using the same data set was conducted. It was found that the SVM classifier provided the best recognition performance with an accuracy of 100%, which exceeded the accuracy of 80% given by the BP classifier.

Key words: Corn seedling, weeds, texture, support vector machine, recognize.

INTRODUCTION

Weed species retard the growth of the crop and reduce farm yields. To control the growth of weed species, a large number of herbicides are used in agriculture fields, which results in drinking water and environment pollution. Some previous attempts have been done to apply machine vision in order to solve this problem (SØgaard, 2005; Tellaeche et al., 2008). However, most of the work has been done with an indoor condition or controlled illumination, not taking into account natural sunlight and complicated backgrounds.

With the development of image processing technology, numerous image-processing algorithms are available for extracting some feature parameters that recognize the weeds, that is, color, shape, and texture (Lee et al., 1999; Burks et al., 2005; Chou et al., 2007; Meyer et al., 2008). Especially, the texture features are widely used to analyze and identify the objects. Various statistical and artificial intelligence methods have been used for recognizing or classifying the weeds, such as artificial neural networks (Marchant and Onyango, 2003; Burks et al., 2005), Bayesian approach (Marchant and Onyango, 2003; Ukrit et al., 2006; Tellaeche et al., 2008). Among them, Burks et al. (2005) evaluated the neural-network classifiers using texture features, such as second moment, mean intensity, variance, correlation, product moment, inverse difference, entropy, sum entropy, difference entropy, information correlation measure No. 1 and information correlation measure No. 2, as input vectors. They find that the back-propagation neural-network classifier gives higher classification accuracy, which is 97% and provides less computational requirements than counter-propagation and radial basis function neural-network classifiers.

In this work, we assess the texture features of weeds and corn seedlings in experimental fields for identification because the texture reflects the changes in intensity pixel values, which might contain information about color and the geometric structure of objects. We use support vector machine classifier to identify weed-corn seedlings. The Support Vector Machines (SVM) algorithm is a new and attractive approach to data modeling in artificial intelligence. SVM has been widely applied to classification problems (Li et al., 2004; Karimi et al., 2006; Dhanalakshmi et al., 2009). SVM finds an optimal separa-

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Table 1. The average values of red, green, blue components of pixels between plants and soil.

	Soil				Plant				
	Stone	Straw	Wet	Dark	Corn	Copperleaf	Rice galingale	Chinese sprangletop	Yerbadetajo
Mr*	181.89	157.39	158.50	68.24	131.61	127.32	135.65	133.67	129.26
Mg	161.72	132.94	143.32	52.79	169.87	174.78	173.67	167.89	171.44
Mb	130.90	95.79	131.71	33.35	86.32	120.55	98.56	92.56	124.58

Mr, Mg, and Mb: the mean values of red, green, blue components of pixels in each image, respectively.

ting hyper-plane to separate the two classes with a maximal margin. Moreover, it is simple to use and only a few parameters need to be adjusted by the users. The objective of this study is to construct a new detection model by means of the excellent classification power of SVM technique to identify weed and corn seedling.

This paper is organized as follows. First, we describe the experimental conditions used to capture weed-corn seedling images. Then, image segmentation is done by transforming the red, green, blue color images to grayscale intensity images and texture parameters measured from these gray images are defined. The details of them are presented in Section 2. Next, we present the results obtained from the SVM classifier with different features and compare its performance with that of the BP classifier. Finally, section 5 concludes this paper.

MATERIALS AND METHODS

Image acquisition

To acquire the original images, we used a digital camera in this work. Color images were taken vertically from above with a 640 × 480 pixels resolution under natural lighting conditions in the experimental field in China. To explore the effect of the weather and illumination, pictures were captured in different weather conditions. The camera was mounted on the top of the tripod when photos were taken. The vertical distance from the camera to the ground was 50 cm. The most dominant weeds in corn fields in China were Yerbadetajo (*Eclipta prostrata L.*), Chinese Sprangletop (*Leptochloa chinensis* (L.) Nees), Copperleaf (*Acalypha australis* L.), Rice galingale (*Cyperus iria L.*). One or more the sub images (256 × 256 pixels) respectively containing one weed seedling or corn seedling were 'cut out' from each obtained image, stored as 24 bit color images in computer memory.

Color analysis and image segmentation

The initial goal in the present weed detection task was to divide the different pixels of the image into two classes: background and plant. To accomplish this goal, differences in red, green, blue components of pixels between vegetation and non-vegetation were used. To explore the effect of light change (sunny or cloudy) and different background including stones, straw and others, even wet and dry soil, some sub-images (20 × 20 pixels) from the original images, at random, were extracted to obtain their statistic values, that is, mean values of red, green, blue channels of background and vegetation (corn/weed) (Table 1).

From Table 1, we could see that the relationship involving Mr, Mg, Mb of the soil (including stone, straw, wet and dark) was Mr>Mg>Mb, whereas that of the plants (corns or weeds) was Mg>Mr>Mb. Therefore, we proposed the following methods to segment vegetation from soil, which was not sensitive to the effects of light change and different background. The formula was given as follows:

$$f(i,j) = \begin{cases} 2\times green - red - blue & ((green > red)\ \&\&(green > blue)) \\ 0 & (else) \end{cases} \quad (1)$$

Where; red, green and blue is the pixel intensity in the red, green, blue channel, respectively, and $f(i,j)$ is the intensity of the resulting grey scale pixel at location *(i, j)*.

The aim of image segmentation was to locate certain objects of interest, which, in this case, were the weeds or corn seedlings. Then through the above transformation, plants were fast segmented from soil to reduce or avoid false detection and the background was also normalized (black). In other words, 24-bit red-green- blue (RGB) images were transformed to 8-bit gray scale images and the intensity value of the pixels of the background was equal to 0. An example of image segmentation using eq. (1) was shown in Figure 1.

Feature extraction

The aim to the analysis was to classify the objects derived by image segmentation into a defined number of classes according to their specific features. In this study, texture features were chosen to identify the weed/corn. Some textural parameters were extracted using MATLAB7.4 with DIPUM toolbox and computer program, as follows (Gonzalez et al., 2004):

Mean: $$m = \sum_{i=0}^{L-1} z_i\, p(z_i) \quad (2)$$

Standard deviation: $$\sigma = \sqrt{\sum_{i=0}^{L-1} (z_i - m)^2\, p(z_i)} \quad (3)$$

Smoothness: $$R = 1 - 1/(1 + \sigma^2) \quad (4)$$

Third moment: $$\mu_3 = \sum_{i=0}^{L-1} (z_i - m)^3\, p(z_i) \quad (5)$$

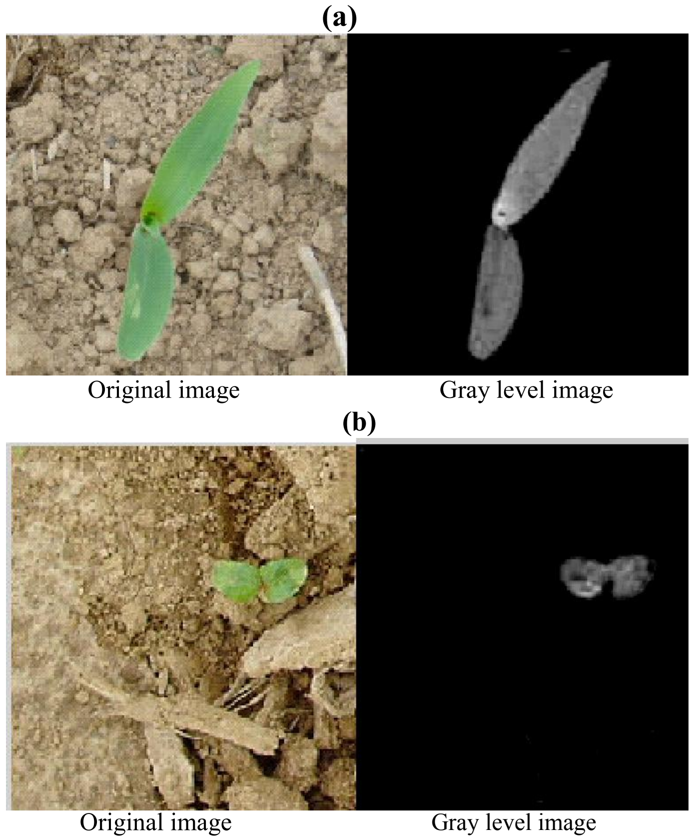

Figure 1. Examples of original sub-images and their gray level images using Equation (1). (a) Corn seedling image. (b) The weed (Copper-leaf) image. Left, original RGB images. Right, the corresponding gray level images (where vegetation (corn seedling or weed) was gray, background was black).

Uniformity: $$u = \sum_{i=0}^{L-1} p^2(z_i) \quad (6)$$

Entropy: $$e = -\sum_{i=0}^{L-1} p(z_i)\log_2 p(z_i) \quad (7)$$

Where; L is the number of possible gray levels in an image, z is a random variable representing the gray level, and $p(z_i)$ is the histogram of the gray levels image.

Others were obtained from Gray Level Co-occurrence Matrix (GLCM) which was derived from the gray level images (see section 2.2). An element $p(i,j\,|\,d,\theta)$ of a GLCM of an image represents the relative frequency, where i is the gray level at location (*x, y*), and j is the gray level of neighboring pixel at a distance d and an orientation θ from location (*x, y*). In this work, we supposed that the GLCM of distance (d) is equal to 1 pixel, and the orientations (θ) are 0°, 45°, 90° and 135° respectively.

Contrast: $$F_1 = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} |i-j|^2\, p(i,j\,|\,d,\theta) \quad (8)$$

Energy $$F_2 = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p^2(i,j\,|\,d,\theta) \quad (9)$$

Homogeneity: $$F_3 = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \left(p(i,j\,|\,d,\theta)/(1+|i-j|)\right) \quad (10)$$

Correlation: $$F_4 = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \left((ij\,p(i,j\,|\,d,\theta) - \mu_x\mu_y)/\sigma_x\sigma_y\right) \quad (11)$$

In Eq.11 $\mu_x = \sum_{i=0}^{N-1} i \sum_{j=0}^{N-1} p(i,j\,|\,d,\theta)$ $\mu_x = \sum_{j=0}^{N-1} j \sum_{i=0}^{N-1} p(i,j\,|\,d,\theta)$

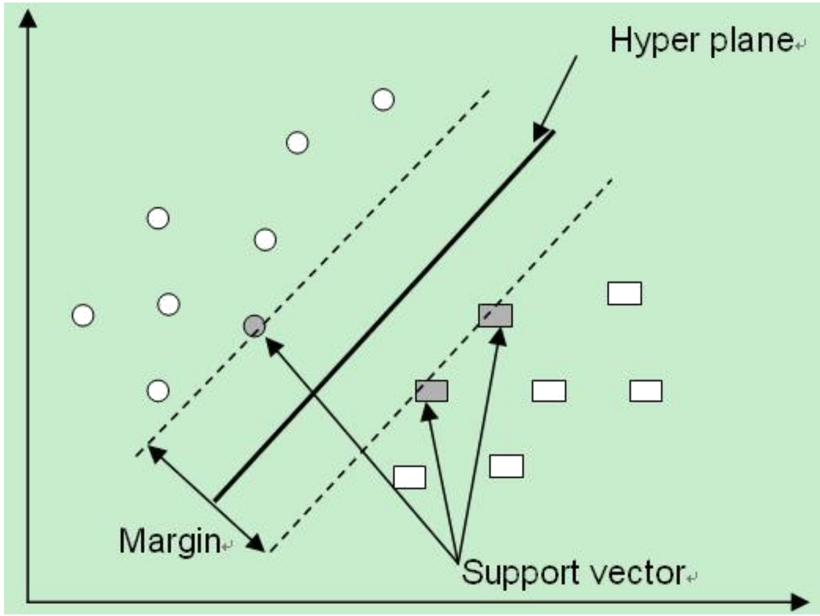

Figure 2. Hyper-plane of two-class case.

$$\sigma_x{}^2 = \sum_{i=0}^{N-1} (i-\mu_x)^2 \sum_{j=0}^{N-1} p(i,j \mid d,\theta),$$

$$\sigma_y{}^2 = \sum_{j=0}^{N-1} (j-\mu_y)^2 \sum_{i=0}^{N-1} p(i,j \mid d,\theta)$$

Where; N is the number of intensity levels in an image.

In this paper, the means of 4 texture features obtained from GLCM, that is, f_1, f_2, f_3 and f_4, were used to replace the original values (F_1, F_2, F_3 and F_4). For example, 10 texture feature values (Mean, Standard deviation, Smoothness, Third moment, Uniformity, Entropy, mean of Contrast, mean of Energy, mean of Homogeneity, and mean of Correlation) of the corn seedling image in Figure 1(a) were 10.5473, 32.6099, 0.0161, 1.5535, 0.8134, 1.0666, 39.7092, 0.8066, 0.9362 and 0.9814, respectively; and those of the Copperleaf image in Figure 1(b) were 2.6995, 16.8968, 0.0044, 0.4704, 0.9489, 0.3340, 9.4659, 0.9470, 0.9805 and 0.9835, respectively.

The Support vector machine (SVM) method

The Support Vector Machine is a new machine learning technique based on the statistical learning theory. It is developed to solve the classification problem. The main goal of classification using SVM, in fact, is to build a function (that is, hyper-plane) that can separate the two classes at a maximal distance (margin). Then, the best decision surface is determined by only a small set of points termed the support vectors (in gray, Figure 2), and the other points can be removed from the whole set. A simple two-class classification problem is given as follows:

Given a training data of the form $\{(x_1, y_1), \ldots, (x_k, y_k)\}$, where k is the number of training samples, and $y_i \in \{+1, -1\}$ is class label. And the linear classification function is:

$$f(x) = \langle w, x \rangle + b \qquad (12)$$

Where; w is a weighted vector, b is bias value.

In Figure 2, the optimal classifying plane (in bold) and the support vectors are shown. It is clear that support vectors only affect the equation of the optimal separating hyper-plane, that is, $\langle w, x \rangle + b = 0$. Moreover, the distance between the two supporting planes (dotted lines, in Figure 2) can be obtained and is equal to $2/\|w\|$, where $\|w\|$ is the Euclidean norm of w.

In order to make the margin maximize which is actually minimizing the following problem:

Minimize: $\phi(w,b) = \|w\|^2 \qquad (13)$

Subject to: $y_i[(\langle w, x_i \rangle + b)] - 1 \geq 0$

With Lagrange function

$L = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{k} \alpha_i \{y_i [\langle w, x_i \rangle + b]\} + \sum_{i=1}^{k} \alpha_i$, we can obtain the dual optimization problem:

Maximize: $w(\alpha) = \sum_{i=1}^{k} \alpha_i - \frac{1}{2} \sum_{i=1}^{k} \sum_{j=1}^{k} \alpha_i \alpha_j y_i y_j \langle x_i, x_j \rangle \qquad (14)$

$$\text{Subject to: } \sum_{i=1}^{k} y_i\alpha_i = 0, \alpha_i > 0, i = 1,2,...k$$

In this way, the optimization problem turns to find a quadratic function's extremum with a linear equation and positive constraints. If the optimal solution is α_{i*}, discriminant function (that is, the classification function) is built as follows:

$$f(x) = \langle w^{*}, x\rangle + b^{*} = sign \sum_{i=1}^{k} y_i\alpha_i^{*}\langle x_i, x\rangle + b^{*} \quad (15)$$

Where; b_* is the threshold value.

For the nonlinear case, we can project the original space into a higher dimension space in which the SVM can construct an optimal separating hyper-plane. Let us consider a function $\phi(x)$, such that $F = \{\phi(x) : x \in X\}$ is the feature point corresponding to the data item x. For SVM, the kernel function represented as $K(x, z) = (\phi(x), \phi(z)), \forall x, z \in X$ replaces theinner product (x, z). In the new feature space, the objective function and the discriminant function become:

$$w(\alpha) = \sum_{i=1}^{k} \alpha_i - \frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k} \alpha_i\alpha_j y_i y_j K(x_i, x) \quad (16)$$

Subject to: $\sum_{i=1}^{k} y_i\alpha_i = 0, 0 \le \alpha_i \le C, i = 1,2,...k$

$$f(x) = sign \sum_{i=1}^{k} y_i\alpha_i K(x_i, x) + b \quad (17)$$

Where; C is the parameter that affects the quality of classification.

In this study, if $f(x)$ >0, input vector x belongs to one class (the corn seedling); if $f(x)$ <0, input vector x belongs to the other (the weed).

The most commonly employed kernel functions in SVM classifier can be: linear, polynomial and radial basis function. In this work, the Radial Basis Function (RBF), most commonly used in SVM classification problems, is used as $K(x_i, x)$ because of its good general performance and the few parameters, it is defined as:

$$K(x, y) = \exp(-\|x - y\|^2 / 2\sigma^2) \quad (18)$$

Where; σ is a kernel function parameter.

RESULTS AND DISCUSSION

The image samples used in our experiment consisted of 66 images, including 30 corn seedling images and 36 weed images. The above mentioned texture features were obtained using MATLAB software for each image to build the feature data set, including corn subset and weed subset. For the feature data set, we randomly chose, for each class, 60% of the subset to build the classifier and the remaining 40% for testing purposes. In other words, the set was divided into training set and testing set at random. The selected 10 feature parameters obtained from GLCM and histogram of gray level images were used as input vectors of SVM classifier in this work. However, we considered 2 cases about input vectors of the classifier: all texture features and partial texture features. The partial features selections included the features selected by Principle Component Analysis (PCA), those obtained from GLCM and those derived from the histogram respectively. The contribution rates of first and second principle component by PCA in the experiment were 53.29 and 44.04%, respectively. Based on this, we just selected first and second components to approximate-ly represent the objects and took the corresponding variables as input vectors. Eight feature vectors used in SVM classifier were obtained by linear combination of 10 texture features using PCA.

Identification using SVM classifier with different feature selections

In SVM classifier, the different feature selections were discussed in the experiment. The parameter C and σ were obtained on condition that the total error was minimum: C = 1,000 and $\sigma = 1$. Thus, the two parameters were used in all experiment. The correct identification accuracy was given by the correct identified numbers including the weeds and the corns divided the total sample numbers. The classification accuracies with different input parameters were shown in Table 2.
As shown in Table 2, the SVM classifiers used F8 and F10 as input vectors also achieved the best training and testing accuracy of 100%, whereas in the same data set the classifier with F4 gave a recognition rate 92.59% and the classifier associated with F6 even provided 93.94% training rate and 92.31% testing accuracy. For experimen-tal simplicity, the classifier associated determined by F8 was chosen in the following experiment.

Comparing classification results using different classifiers

We obtained the result using Back-propagation (BP) neural-network in the same data set. The BP neural-network classifier was implemented using functions of MATLAB 7.4. In BP classifier, consisting one input layer, one hidden layer and one output layer. The number of

Table 2. Classification results using different feature vectors in SVM classifier.

Input vectors[1]	nSV[2]	Training accuracy (%)	Testing accuracy (%)
F4	32	97.44	92.59
F6	46	93.94	92.31
F8	41	100	100
F10	38	100	100

[1]F4: f_1, f_2, f_3 and f_4 as input vectors. F6: m, σ, R, μ_3, u and e as input vectors. F8: the features by PCA. F10: all the texture features. [2]the number of support vectors obtained from SVM classifier.

Table 3. Classification results using SVM classifier and BP classifier.

Classifier	nSV[3]	Accuracy [4](%)
SVM	41	100
BP		80

[3]the number of support vectors obtained from SVM classifier. [4]the total correct identification rate.

nodes in input layer was the number of feature parameters. There were two outputs in this work. The expect output was [1, 0] for the corn and [0, 1] for the weed. Number of the nodes in hidden layer was calculated by (Visen et al., 2002):

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

Where; n_i is the number of the input nodes, n_o is the number of the output nodes and y is the number of input samples in the training set. In the experiment, input nodes, hidden nodes and output nodes were 8, 11, and 2, respectively. The number of training epochs was 185 and the goal got 0.00586. The functions used in BP classifier were ‘tansig’, ‘logsig’ and ‘trainlm’. The result had been shown in Table 3.

The result showed that the BP classifier provided the testing accuracy of 80%, whereas the SVM classifier gave the best testing accuracy of 100% in the same feature set. In two-case classification problem, the performance of the SVM classifier had certain advantage over that of the BP classifier.

Conclusion

This study demonstrated the capability of Support Vector Machines method to identify the in-field weed/corn images in early growth stage. A classification accuracy ranging 92.31 to 100% was achieved with different feature selec-tions. The SVM classifier associated with more features provided better accuracy, whereas the feather space dimensions could be reduced by PCA and the accuracy was not be affected. In comparison of the result obtained with a BP neural-network model (80%) in the same data set, our result was much better which clearly demonstrated the superiority of support vector machines methodology in resolving classification problems of precision agriculture.

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