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Application of Co-occurrence Matrix on Wavelet Coefficients for Crop-weed Discrimination

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Abstract

The objective of this study was to discriminate the main crop from the common weeds in the field. Textural image analysis was applied to differentiate between the crop and the weeds. In the textural analysis, images were divided in square tiles, and were subjected to a wavelet transform. Wavelet transformation of digital images produces several spatial orientations which are highly effective in analyzing the information content of the images. In this study for each sub-band of wavelet coefficient, co-occurrence matrix was constructed to extract appropriate features for classification. Energy, entropy, contrast, homogeneity and inertia features were extracted from each orientation of the co-occurrence matrix. Finally, these features were fed into a multi-layer perceptron neural network to classify corn and four species of common weeds in the corn field. One hundred images were captured in normal condition of the plants in the field and were used to verify the ability of the proposed method in crop-weed discrimination. Results showed that this technique was able to distinguish the corn plants with an accuracy of 99.9%, and 96% for the weeds.

Keywords: Image processing, Texture feature extraction, Wavelet transforms, Weed detection.

INTRODUCTION

The goal of precision farming is to maximize profitability and minimize environmental damage. Much research has investigated strategies to control weeds with less herbicide to reduce production costs and to protect the environment. A verity of visual characteristics that have been used in plant identification can be divided into three categories: Morphology, Spectral Reflectance and Texture.

Shape feature-based weed species classification has been conducted by numerous researchers (Guyer et al. 1986, 1993, Franz et al. 1990, Woebbecke et al. 1995b; Zhang and Chaisattapagon, 1995; Yonekawa et al. 1996). This type of method has limited application to whole canopies as it demands analysis on the individual seedling or leaf level.

Vrindts and De Baerdemaeker [12] 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.

In more general texture research, Haralick et al [8] used co-occurrence matrices to classify sandstone categories in photomicrograph images and wood, lake, road, etc., in aerial Texture features of weed species have been applied in distinguishing weed species by Meyer et al. (1998). In this research, four classical textural features derived from the co-occurrence were used for discriminant analyses. Grass and broadleaf classification had accuracy of 93% and 85%, respectively. Individual species classification accuracy ranged from 30% to 77%.

Weed control is often mentioned as a likely area of application of agricultural robots. One of the earliest references is the robot of Tillett et al. [11] in cauliflower. In some recent literature, the focus was on weeds in sugar beet [2].

In organic farming, this troublesome grassland weed is best controlled by manual removal of the plants, possibly combined with grassland renewal and rotation with a grain crop [13].

A motorized tool exists to shred dock plants [13] but operating this tool is physically demanding. A robot that detects dock plants and destroys them using this tool would be a logical development. Ahmad and Kondo [1] used uniformity analysis to detect the presence of broad-leaved weeds in lawns. Gebhardt and Kühbauch [4] implemented the algorithm of Ahmad and Kondo and found that it performed reasonably well for docks in grass, but at several seconds per image it was too slow to be usable for real-time detection.

Gerrit Polder et al [5] used textural image analysis to detect weeds in grass. In the textural analysis, images were divided in square tiles, which were subjected to a 2-D FFT. The power of the resulting spectrum was found to be a measure of the presence of coarse elements (weeds). Application of a threshold made it possible to classify tiles as containing only grass or as containing a weed.

Thus, the objective of the work described here was to develop a vision-based algorithm to identify textural features for detecting corn plant and to develop an algorithm for separating corn using an ANN. With this method we can remove all species weeds by using mechanical weeding machine without using herbicides in field. The overall aim of our work is to develop a robot for the detection and control of weeds in corn fields.

MATERIALS AND METHODS

Software Development

The images were taken in crop fields at early stage of growth, in natural variable lighting conditions at a distance of 0.9-1 meter perpendicular to the ground. The algorithm was developed in MATLAB 7.7 (Math Works 2008). Images resolution was 640 pixel by 480 pixel. The pictures were taken at several randomly chosen locations in the field.

Textural Features Extraction

The Theory of Wavelet

Wavelets are mathematical functions that cut up data into different frequency components and then study each component with a resolution matched to its scale [10]. They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes. Wavelets were developed independently in the fields of mathematics, quantum physics, electrical engineering, and seismic geology. Interchanges between these fields during the last ten years have led to many new wavelet applications such as image compression, turbulence, human vision, radar, and earthquake prediction.

Wavelet families X(a, b) is the set of basic functions generated by dilation and translation of a unique mother wavelet X (t):

$$x_{a,b}(t) = |a|^{-1/2} x\left(\frac{t-b}{a}\right) \quad (1)$$

Where t is the time and b is the scale and translation parameter respectively. The wavelet becomes narrower when an increases and finer information could be captured. A two dimension wavelet transform is the extended version of one dimension wavelet transform, where the decomposition is iteratively done along the vertical direction followed by the horizon direction. The 2-D discrete wavelet transform (DWT) represents an image in terms of a set of shifted and dilated wavelet functions $\{Q^{LH}, Q^{HL}, Q^{HH}\}$ and scaling functions Q^{LL} that form an orthonormal basis for $L^2(R^2)$. Given a J-scale DWT, an image x(s, t) of N*N is decomposed as:

$$x(s,t) = \sum_{k,i=0}^{N_{J-1}} u_{J,k,i} Q^{L}_{J,k,i}(s,t) + \sum_{B\in\beta} \sum_{j=1}^{J} \sum_{k,i=0}^{N_{j-1}} w^{B}_{j,k,j} Q^{B}_{j,k,i} \quad (2)$$

These wavelet coefficients provide a paramour view of information in a simple way and a direct estimation of local energies at different scales.

Guoliang Fan [6], there are three major applications of texture processing, Classification, segmentation, and synthesis. Classification involves the identification of the type of a given homogeneous region. Segmentation attempts to produce a classification map of the input image where each uniform textured region is identified with the localized texture boundaries. Texture synthesis is often used for image compression, where the goal is to render object surfaces as visually similar to the real ones or as realistic as possible. In the following experiments, we use Db4 as the wavelet in our transform. Researchers found that the Db4 wavelet is much more suitable than other wavelets and the recognition rate attained shows more higher performance in the classification.

The Theory of Co-occurrence matrix

For example, the probability of a pixel obtaining a certain value may be calculated directly from the data by computing the histogram of the image and normalizing it by dividing by the total number of pixels in the image. This approach, obviously, destroys any spatial information, so it destroys the spatial aspect of texture patterns and only retains their brightness information. However, what makes texture recognizable as texture is the spatial arrangement of relative brightness values. This implies that one has to capture both spatial and relative brightness information. So, instead of representing the probability of a pixel having a certain value, we should be representing the joint probability of certain sets of pixels having certain values. Such matrices are called co-occurrence matrices as they convey information concerning the simultaneous occurrence of two values in a certain relative position.

Mathematically, a co-occurrence matrix C is defined over an n x m image I, parameterized by an offset (Δx, Δy), as:

$$C_{\Delta x,\Delta y}(i,j) = \sum_{p=1}^{n}\sum_{q=1}^{m} \begin{cases} 1, \text{if } I(p.q) = i \text{ and } I(p+\Delta x, q+\Delta y) = j \\ 0, \text{otherwise} \end{cases} \quad (3)$$

The value of the image originally referred to the grayscale value of the specified pixel. The value could be anything, from a binary on/off value to 32-bit color and beyond. Note that 32-bit color will yield a 232x232 co-occurrence matrix. Really any matrix or pair of matrices can be used to generate a co-occurrence matrix, though their main applicability has been in the measuring of texture in images, so the typical definition, as above, assumes that the matrix is in fact an image. It is also possible to define the matrix across two different images. Such a matrix can then be used for color mapping. Note that the (Δx, Δy) parameterization makes the co-occurrence matrix sensitive to rotation. We choose one offset vector, so a rotation of the image not equal to 180 degrees will result in a different co-occurrence distribution for the same (rotated) image. This is rarely desirable in the applications co-occurrence matrices are used in, so the co-occurrence matrix is often formed using a set of offsets sweeping through 180 degrees (i.e. 0, 45, 90, and 135 degrees) at the same distance to achieve a degree of rotational invariance.

Feature extraction on coefficient of co-occurrence matrix

Co-occurrence matrices are very rich representations of an image. One may use directly some of the elements of co-occurrence matrices to characterize a texture, particularly for the cases where some reduction in the number of grey values has already been applied. In particular, ratios of elements of the co-occurrence matrix have been shown to be good texture descriptors. This is because they capture the relative abundance of certain image characteristics. The classical approach, however, is to compute certain characteristics of the co-occurrence matrix. The co-occurrence matrix, after all, corresponds to a joint probability density function and one can characterize probability density functions by computing a few statistics from them. The most commonly used features computed from each orientation of the co-occurrence matrix are listed below. In all cases, the co-occurrence matrix has been normalized by dividing all its elements by the total number of pairs of pixels considered.

$$\text{Energy} = E(d,\theta) = \sum_{i,j} c^2(i,j) \quad (4)$$

$$\text{Entropy} = H(d,\theta) = \sum_{i,j} c(i,j)\log c(i,j) \quad (5)$$

$$\text{Inertia} = I(d,\theta) = \sum_{i,j} (i-j)^2 \log C(i,j) \quad (6)$$

$$\text{Local homogeneity} = L(i,j) \sum_{i,j} \frac{1}{1+(i-j)^2} C(i,j) \quad (7)$$

$$\text{Contrast} = \frac{\sum_{i,j} (i-j)^2 * C(i,j)}{(j-1)^2} \quad (8)$$

Training and Classification

A back propagation network was used for ANN classifier and it is a kind of non-linear method widely used in recognition and forecasting. They are composed of simple elements which operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. The network is adjusted, based on a comparison of the output and the target, until the network output matches the target.

Features of 20 images of corn and 30 images of weeds (all vegetation without corn) in the image were used to build ANN classifier. In the input layer, each input node was assigned to value of features. One and two hidden layer was tested. There were one outputs in this ANN. Number of hidden nodes were changed from 5 to 25. The expected output in the training file was {1} for corn, and {0} for all weeds in the image. The proposed ANN model is shown in Fig 1.

RESULTS AND DISCUSSION

At the first we choose 20 images of corn and 30 images of common weeds (Amaranthus, Alhagi maurorum, Chenopodium album L, Convolvulus arvensis L).Images were divided in square tiles, and were subjected to a wavelet transform. In this study for each sub-band of wavelet coefficient, co-occurrence matrix was constructed. Energy, entropy, contrast, homogeneity and inertia features were extracted from each orientation of the co-occurrence matrix. Masking was used for extracting feature from each orientation of co-occurrence matrix. Numerous sizes of mask was test from 10*10 to 50*50. Results showed that size of mask 13*13 is suitable for this application. Thus, 5 features were extracted and the feature vectors were saved to a file before neural network training. The data which obtained from features extractor are displayed in Fig 2.

Log sigmoid transfer functions were applied to each processing element. Two hidden layer was tested. There were one outputs in this ANN. Number of hidden nodes were changed from 5 to 25. Finally 20 images of corns and 30 images of weeds were used to evaluate the ANN performance after training. Accuracy of both the training data and test data set were obtained by Equation (9):

$$\text{Accuracy} = \frac{\text{Number of correctly classified samples}}{\text{Number of samples}}$$

Table I and Table II show the results of training and tests. The test data set were classified with 98% accuracy. The fewer number of input nodes and hidden nodes, the less time is required for image processing. It shows that the same result could be achieved with less time.

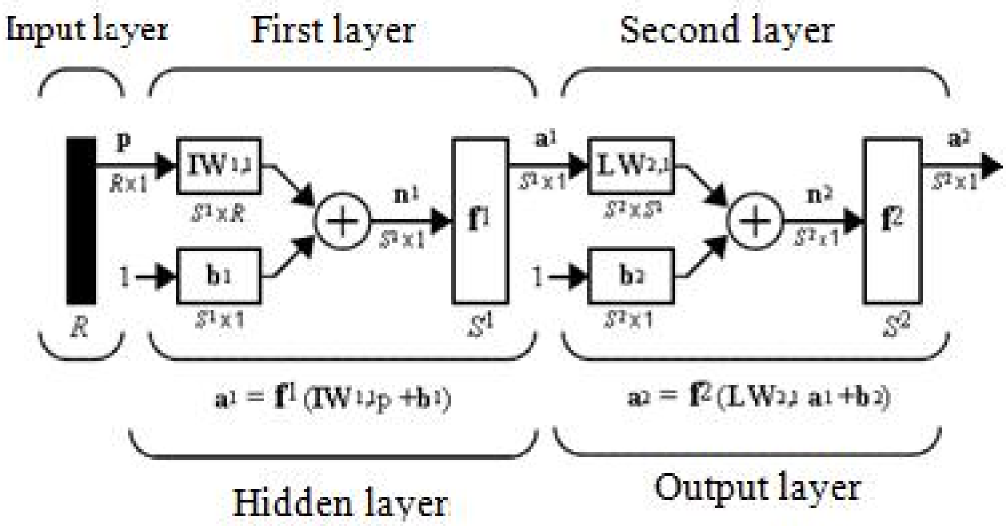

Fig. 1. Artificial Neural Network Model

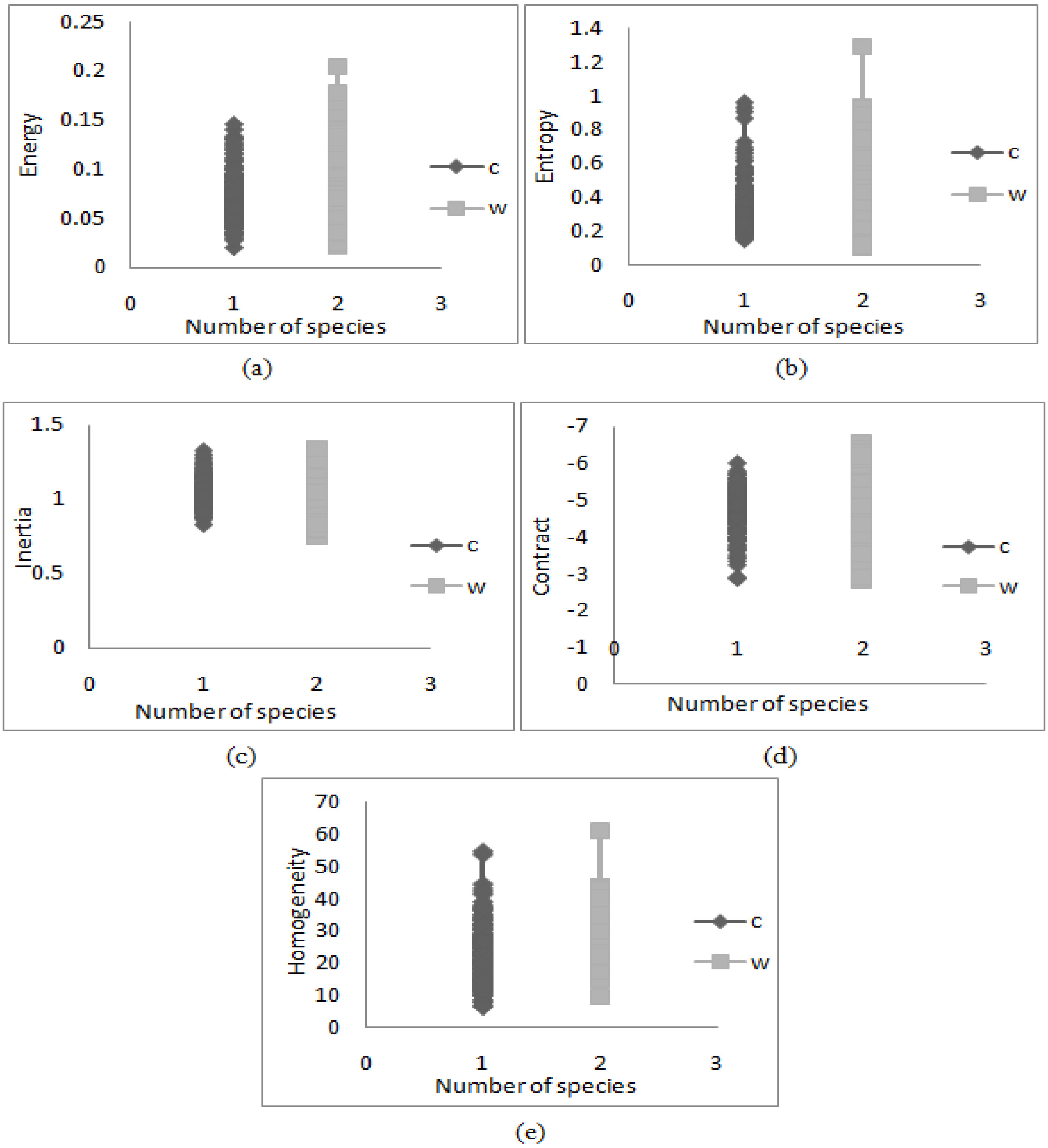

Fig.2. Extracted values of various features for species (1) C (Corn) and (2) W (Weeds or other objects), (a) Energy, (b) Entropy, (c) Inertia, (d) Contract and (e) Homogeneity

Table 1. Classification results of ANNs with different topologies and 5 input features (accuracy %)

	Neural network structure					
	20-5-1	20-10-1	20-15-1	20-15-15-1	20-20-20-1	20-25-25-1
Corn	62%	50.5	80%	94%	99.4%	99.8%
Weeds	76%	96%	80.57%	93.5%	96.45%	96.9%

Table 2. Classification results of ANNs with different topologies and 5 input features (accuracy %)

	Neural network structure 20-25-25-1	
Plant	**Corn**	**Weeds**
Corn	99.9%	0%
Weeds	4%	96%

CONCLUSION

We introduced in this paper a new algorithm and recognition method, which employs the co-occurrence matrix features on wavelet coefficient of images. A new algorithm for the crop detection and mechanical weeding in a corn farm was developed. The five features were obtained from the co-occurrence matrix of corn and common weeds in the field and ANN model was developed to distinguish the corn from the weeds with 99.9% accuracy.

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