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Crop-Weed Discrimination Via Wavelet-Based Texture Analysis

Sajad KİANİ
Department of Automotive Engineering, Islamic Azad University, Khomeini shahr Branch, Isfahan, IRAN

***Corresponding Author**
e-mail: Sajad.kiani@iaukhsh.ac.ir

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Abstract

The worldwide problem of environmental pollution caused by excessive use of herbicides and the increasing cost of chemicals necessitates finding alternative methods for crop protection. In order to reduce the quantities of herbicides applied to fields, we propose to exploit the advantages of image processing to automatically detect and localize the crops and to remove all other undesired plants growing within rows and between two crops. Wavelet transformation of digital images discriminates several spatial orientations and it is very effective in analyzing the information content of images. In this study wavelet Analysis is used to extract appropriate features for classification. The mask is calculated for each sub-band of wavelet transform. Then, energy, entropy, contrast, homogeneity and inertia features are extracted from each sub-band. Finally, these features are feed into a multi-layer perceptron neural network to classify Corn and Weeds from each other commonly found in corn farms. Results showed that this technique was able to discriminate corn plants with a very significant accuracy in comparing with the state-of-the art techniques.

Keywords: Image processing; Feature extraction Texture; Wavelet transform; weeds

INTRODUCTION

Weed control is one of the expensive and time-consuming activities in agriculture, and long-term use of herbicide could damage people, 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, in precision farm fields, it is very important to identify weeds from crops. Information on crop and distribution within the field is necessary to implement spatially variable herbicide application or other device for mechanical weeding-thinning.

Wavelet analysis of signals is increasingly becoming a popular tool in signal processing. Signal processing includes noise removal, compression, feature extraction, and reconstruction. Digital image signals can be two dimensional signals such as optical visible images, ultrasonic images, X-ray images or three dimensional signals such as hyper spectral images, computed tomography (CT) images, and magnetic resonance images (MRI). Many kinds of machine vision technology have been employed, mainly including spectral devices and digital cameras. Some researchers have proposed different methods for recognizing weeds in crops

Local spectral properties and shape characteristics of plant leaves were used to discriminate between several weed species [6]. This study was limited to the identification of weed seedlings in growth room conditions.

Some combinations of color and shape features were used for sugar beet weed segmentation [1]. They evaluated shape features for single plants and showed that plant recognition based on color vision is feasible with three features and a 5-nearest neighbor's classifier. Color features could solely have up to 92% success rate in classification. This rate increased to 96% by adding two shape features.

Textural image analysis was used to detect weeds in grass [8]. 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. They implemented the algorithm that developed by [13] 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. Compressing a large data set by wavelet transformation before regression is faster compared to directly applying the partial least square (PLS) regression on the original data [10]. Apart from compression, wavelet transform can be successfully applied for separation of overlapping bands, noise removal, smoothing, base line correction, and in removing multicollinearity effect of multidimensional spectra [2].

Wavelet transformation of digital images discriminates several spatial orientations and it is very effective in analyzing the information content of images, texture discrimination, and fractal analysis [12].

Gabor wavelet features of NIR images of apples were extracted for quality inspection and used as input to kernel PCA [14]. Kernel PCA first maps the nonlinear features to linear space and then PCA is applied to separate the image features (solves nonlinearity problem). The PCA transformed data were given as input to a K-nearest neighbor classifier to discriminate healthy apples from blemished apples. Other classification methods such as support vector machine (SVM), PCA, kernel PCA, Gabor PCA were also investigated. However, Gabor wavelet (5 scales and 8 orientations) combined with kernel PCA had the highest recognition rate (90.5%).

Wavelet transform was used to extract textural features for classification of beef tenderness [4]. Multiresolution technique was used to decompose the images to extract the energy as wavelet features. The features were also extracted by Gabor transformation filter from the original as well as wavelet decomposed images. Gabor transformation function is a combination of Gaussian function (used in spatial domain) and Fourier function (used in frequency domain). The features were given as input to discriminant classifier. The Gabor features extracted from the original images gave the poorest classification; however, wavelet energy features gave better classification. Gabor features extracted from the decomposed images gave the highest classification accuracy.Though the Gabor filter reduces the redundancy in extracted sub-image features; selection of several parameters makes it complicated.

The main objectives were to identify features for detecting and positioning crops in the corn fields to develop an algorithm for separating corns from commonly weeds found farms.

METHODOLOGY

Image Acquisition

A digital camera (Canonixus) perpendicularly was used to acquire images in crop fields at an early stage of growth, in natural variable lighting conditions. The suitable stage for the weeding of the direct sowing corn is 25 to 30 days after the emergence. In this time, images of the corn and weeds (Amaranthus, Alhagi maurorum,Chenopodium album L,Convolvulus arvensis L) were taken in the farms of Shiraz University. The pictures were taken at several randomly chosen locations in experimental. The digital images were stored as 24-bit color images with a size of 1600×1200 pixels and saved in RGB color space in the JPG file format. Before testing the discrimination algorithms, pre-processing of the real RGB images was necessary. The analysis of the images was carried out in the office with the Image Processing Toolbox from MATLAB 7.7 (Math Works).

Soil Removal From the Image

First stage is to classify the pixels of images according to the following classes: vegetation, soil. Studies for crop and weed detection have been performed using different spectral bands and combinations for vegetative indices. Some color vegetation indices utilize only the red, green and blue spectral bands. The advantage of using color indices is that they accentuate a particular color such as plant greenness, which should be intuitive for human comparison. In fact, two classes of plant and other things were separated by the Excess Green Index (EGI) defined by the (1):

$$EGI = 2g - r - b \qquad (1)$$

Fig.1.Sample images of corn and weeds after apply function

Where r, g and b were the main color components [5]. Excess green vegetation index provides a near-binary intensity image outlining a plant region of interest. Thus the result of this operation was a Vegetation image. Fig1 shows sample images of corn and weeds after using excess green vegetation index.

The Theory of Wavelets

Wavelet is a most widely used multi-resolution tool in image processing area [8]. Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. 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):

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

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:

$$x(s,t) = \sum_{k,i=0}^{N_{J-1}} u_{J,k,i} Q^{LL}_{J,k,i}(s,t) + \sum_{B\in\hat{a}} \sum_{j=1}^{J} \sum_{k,i=0}^{N_{j-1}} w^{B}_{j,k,j} Q^{B}_{j,k,i} \qquad (3)$$

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

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 [7].

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 [7].

Feature Extraction on Coefficients of Wavelet Transform

There are many approaches to extract texture features in the wavelet-domain with applications to texture analysis and texture synthesis. For example, the most often used texture features are the wavelet energy signatures, which were found efficient for texture classification and segmentation [8].

Five features were extracted from coefficients of DWT [11]. The features of energy, entropy, inertia, local homogeneity and contrast are calculated as:

$$\text{Energy} = E(d,\grave{e}) = \sum_{i\,j} C^2(i,j) \tag{4}$$

$$\text{Entropy} = H(d,\grave{e}) = \sum_{i\,j} C(i,j)\log C(i,j) \tag{5}$$

$$\text{Inertia} = I(d,\grave{e}) = \sum_{i\,j} (i-j)^2 \log C(i\;j) \tag{6}$$

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

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

Using only a small set of the most powerful features will reduce the time for feature extraction and classification. Furthermore, the existing researches have shown that when the number of training samples is limited, using a large feature set may decrease the generality of a classifier.

Training and Classification

A back propagation network was used for ANN modeling 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. Feature of 20 images of corn and 30 images of weeds (all vegetation without corn) in the image were used to build ANN model. In the input layer, each input node was assigned to value of features.

One hidden layer was tested. There were one outputs in this ANN. Number of hidden nodes were changed from 2 to 5. 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

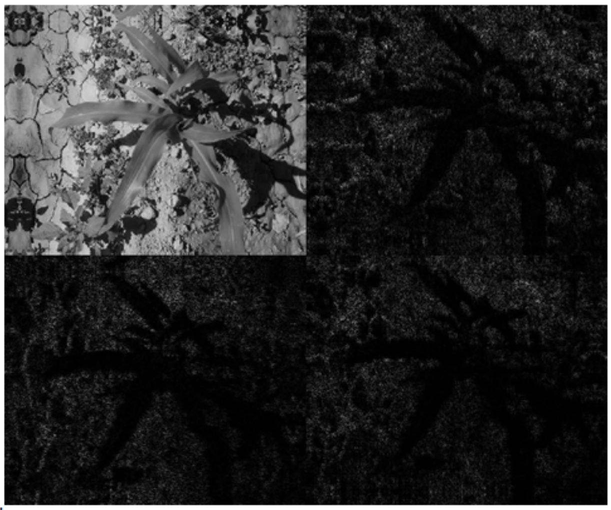

Fig.2. Wavelet transformation sub-bands coefficients

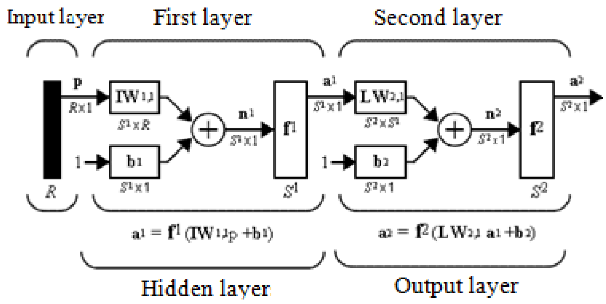

Fig.3.Artificial Neural Network Model

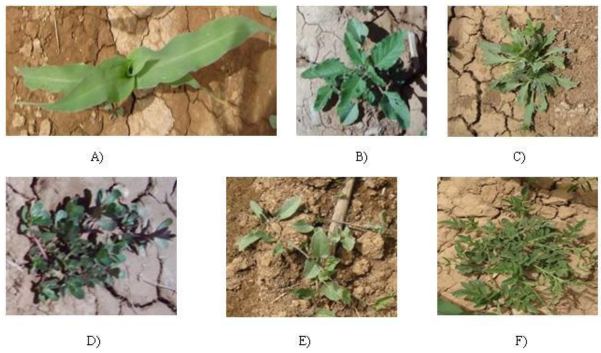

Fig.4.The binary images of the corn and some weeds, (a) Corn, (b) Amaranthus, (c) Alhagi maurorum, (d) Convolvulus arvensis L, (e) Chenopodium album L and (f) Convolvulus arvensis L

RESULTS AND DISCUSSION

Our aim was to find corn, so the 5 features were extracted from the coefficient of wavelet of preprocessed digital images as shown in Fig.4.

At the first we choose 20 images of corn and 30 images of common weeds (Amaranthus, Alhagi maurorum, Chenopodium album L and Convolvulus arvensis L) and all images were processed with the wavelets feature extractor, for each individual class. Masking was used for extracting feature from each sub-band of wavelet transform. Numerous size of mask was test from 10*10 to 50*50. Result show that size of mask 39*39 is suitable for this application. Thus, 5 features were extracting and

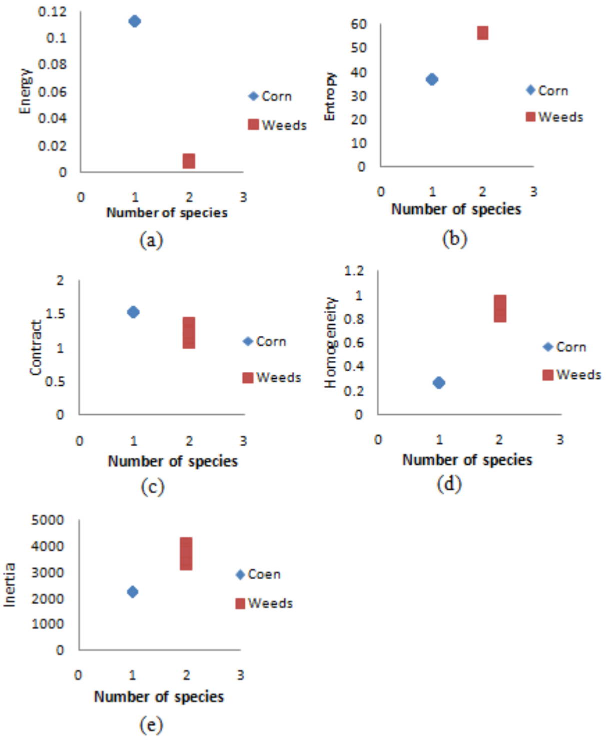

Fig.5. Extracted values of various features for species (1) Corn and (2) Weeds or other objects; (a) Energy, (b) Entropy, (c) Contract, (d) Homogeneity and (e) Inertia

the feature vectors were saved to a file before neural network training. The data which obtained from features extractor are displayed in Fig.5. All features obtained for corn class have an approximately constant value in its range, because corn has a constant color and texture in its leaves.

Thus, all data obtained for each feature for corn are constant value. Log sigmoid transfer functions were applied to each processing element. One hidden layer was tested. There were one outputs in this ANN. Number of hidden nodes were changed from 2 to 5. Training was continued until 800 epochs had been executed.

Fifteen images of corns and 20 images of weeds were used to evaluate the ANN performance after training. Both the training data and test data set were classified with 98.8% percent accuracy that obtained from (9).

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. Comparing these result with other work shown in table III.

CONCLUSION

In precision agriculture, weed detection using image processing techniques has shown a good potential to estimate weed distribution despite the difficulties due to the similarity in spectral reflectance between weed and crop plants, and to the high variability of the natural scenes. We believe that an automatic system could be used for distinguishing crop within common weeds. A new algorithm for the crop detection and mechanical weeding in a corn farm was developed. The five features were obtained from the coefficient of wavelet transform of corn and common weeds in the field and developed

Table.1. Number of Observations (Accuracy %)

Plant	Neural network structure		
	5-2-1	5-3-1	5-5-1
Corn	95%	97%	98.8%
Weeds	93%	96%	97%

Table.2. Number of Observations (accuracy, %)

	Neural network structure 5-5-1	
Plant	Corn	Weeds
Corn	98.8%	1.2%
Weeds	3%	97%

Table.3. Comparing These Result With Other Work

Type of algorithm	**Accuracy (%)**		**Author**
	Corn	***Weeds***	
Weed Detection Using Textural Image Analysis	93	94	Gerrit *Polder et al.* (2003)
Color and shape features	96	96	Astrand *et al.* (2003)
Gabor wavelet features of NIR images	90.5	90.5	Zhu *et al.* (2007)
Our algorithm	97	98.8	

ANN model distinguished the corn from the weeds with 98.8% accuracy.

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