Discrimination of Plant Species Using Co Occurrence Matrix of Leaves

By

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Abstract. *This paper examines the hypothesis that visual features of a plant leaf can provide a unique signature of the plant species. The leaf texture is the classification parameter investigated in this work. Texture signature is derived from a co - occurrence matrix of a leaf segmented from the background. The whole leaf texture is found to provide a basis for a robust discrimination of plant species leaves. This approach is the first step in addressing a very complex problem of identifying plant canopies, by segmenting individual leaves using computer vision.*

Keywords. *Texture, co – occurrence matrix, image processing, weeds, classifier, and leaf.*

INTRODUCTION

Texture analysis is commonly employed in the analysis of satellite images, microscope images and images of textiles. Spectral, textural and contextual features were used (Haralick et. al, 1973) to categorize areas on a satellite image. The use of a window or Area of interest was avoided (Chen and Pavlidis, 1979) by employing a Split and Merge algorithm. Since then, there have been new methods in statistical approaches, spatial interaction or stochastic models (De Backer and Scheunders, 2001; Sarkar et. al, 1997). A comprehensive review of statistical and structural approaches to texture can be found in (Haralick, 1979).

This research work addresses the fundamental requirements of computer vision in biological environment, which is normally very complex. The rapid increase in genetically modified crop plants might also make the application of conventional machine vision sorting methods more applicable to food processing industries as natural variation might be reduced to a level where computer vision could be feasible. The use of plants leaves was to emphasize the complexity of biological shapes in image processing, moreover, species identification and classification can rapidly be achieved by computer vision.

A common feature of the methods employed in most of the texture analysis mentioned above, is the specification of an Area-Of-Interest (AOI). In this paper, we first discuss the shortcomings of this method for determination of useful textural parameters for leaves, and then outline an alternative method based on analysis of a whole leaf. Plant canopies are very complex as shown in Fig 1. The method outlined in this work, that is considering one leaf a time, might lead to an approach which can be used to segment individual leaves from a canopy.

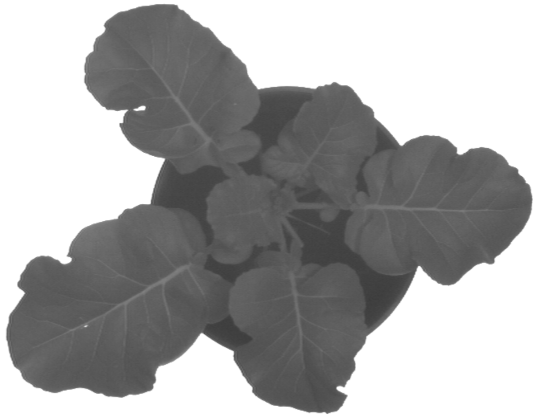


Figure 1. Broccoli plant canopy.

AREA OF INTEREST (AOI) METHOD

As shown in Fig 4, an image is divided into big enough blocks (squares or rectangles) to have meaningful textural information (texture can not be defined for a single pixel) but small enough to encompass one class only. This method is widely applied in the textile industry where the sample tested has relatively homogeneous texture and where there is normally no background.

In natural settings such as satellite images of the earth surface or, in this case, of plants there will usually be a large degree of heterogeneity in texture within the field of view. This demands either a degree of selectivity in choosing an AOI or a method of overcoming the effect of misclassification due to inclusion of regions of different texture in the AOI. For example, in the case of an image of a leaf against a monochrome background, misclassifications occur when the AOI is located on leaf veins or when the AOI is composed partly of leaf and partly of background. The problem is exacerbated if a fixed grid of AOI is used and acceptable results can only be obtained if AOIs are selectively positioned so as to avoid ambiguous areas or those areas are discarded from subsequent discrimination process. One approach to solving this problem is to use the connectivity of classified areas by employing edge detection of veins. This means that, if the textural parameters of an AOI are different to its neighbors but are within a certain location then that area is more likely to contain a vein. This approach will be computationally expensive for real time systems and guiding the texture processing (or texture for segmentation) using unknown shapes will be quite complex. Although (Chen and Pavlidis, 1979) employed a combination of texture segmentation using a split-and-merge algorithm, this method tends to produce square boundaries due to dividing up of the image into quarters, as data structure required by the algorithm. If two or more AOIs are similar then they are combined. Although promising results were obtained, the algorithm developed required complex data structures, and for small regions where texture could not be computed reliably, they used gray level mean of pixels as a similarity feature step.

WHOLE LEAF METHOD

In order to avoid the problems inherent in the AOI method, it is proposed that the whole leaf be used in the textural analysis. The results reported here are based on the following method that assumes that the edge pixels defining the leaf contours are known. The segmentation of the plant leaf as achieved by simple thresholding, any fit edge detection method could have be used.

The leaf types used are shown in Figure 2.

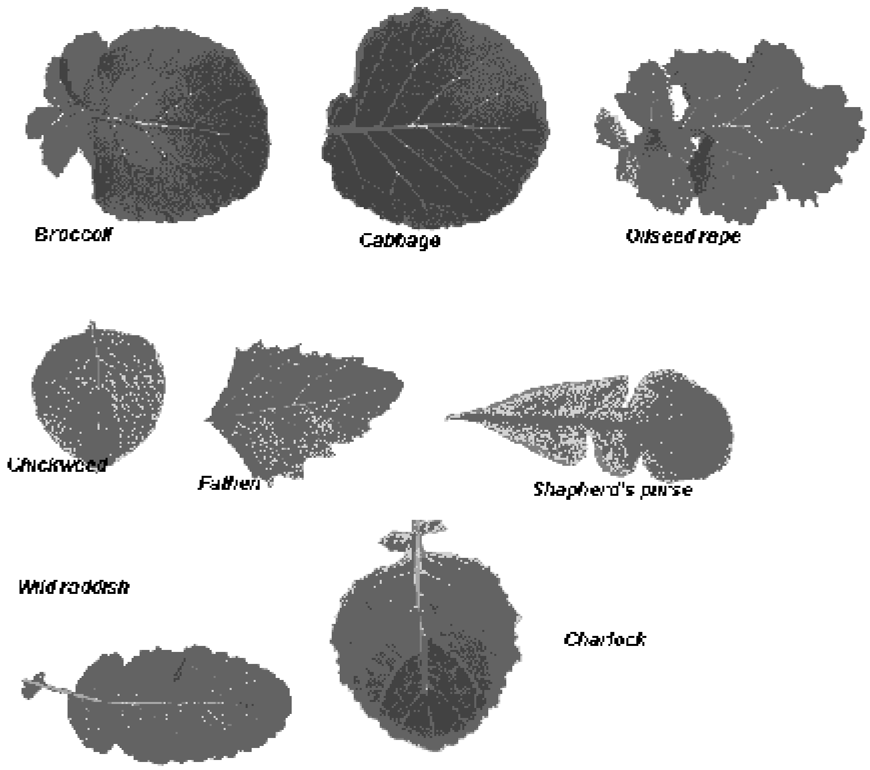


Figure 2. Leaf types used.

ALGORITHM

A gray level co-occurrence matrix based on the pixel intensity of the eight-nearest neighbors was computed for a whole leaf image. The algorithm is similar to the one normally used to generate a co-occurrence matrix, except that, it does not use square or rectangular AOI, that is it is symmetrical. It was realized that only half of the 3 x 3 mask could be used to implement the algorithm since the other half is a mirror image as shown in Figure 3.

135^o	90^o	45^o
0^o	*	0^o
45^o	90^o	135^o

Figure 3. Mask used to implement the algorithm.

Given an image of X and Y spatial domains, L_x by L_y is the set of resolution cells and image **I** is a function which assigns some gray - tone value $G \in \{0,1,2,...,N_{g-1}\}$, (i.e. $N_g = 256$) to each resolution cell. This method is outlined in Haralick *et. al.* 1973. Co - occurrence matrix of relative frequencies P_{ij} of pairs of neighboring pixels in digital images, one having a gray level value of i and the other j (separated by a distance of one pixel i.e. $\Psi=1$). The co-occurrence matrix is a function of both the distance between neighboring pixels (Ψ) and the angular relationship ($\theta = 0^o, 45^o, 90^o, 135^o$) between them. For a $\theta = 90^o$, the un-normalized frequency is defined as:

$$P(i, j, \Psi=1, \theta = 90^o) = Ne[((k, l), (m, n)) \in (L_x \times L_y) \times (L_x \times L_y) \mid k - m| = d, \mid l - n \mid = -d] \quad \text{Equation 1}$$

Where

Ne	denotes the number of elements in a set;
i,j	gray level values;
((k, l), (m, n))	set of neighboring resolution cells;
$L_x = [0,1,2,...,N_{x-1}]$	horizontal spatial domain;
$L_y = [0,1,2,...,N_{y-1}]$	vertical spatial domain;
L_x x L_y	the set of resolution cells ordered by their row-column designations;
N_{x-1} and N_{y-1}	number of pixels in the horizontal and vertical directions.

The following texture features were calculated from the co occurrence matrices and the average value of the four angles used as a feature vector.

Co occurrence Matrix Normalization

$$p(i,j) = \frac{P(i,j)}{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P(i,j)} \qquad \text{Equation 2}$$

Marginal Probability Matrix

$$p_x(i) = \sum_{j=0}^{N-1} p(i,j) \qquad \text{Equation 3}$$

Mean

$$f_1 = \sum_{i=0}^{N-1} i * p_x(i) \qquad \text{Equation 4}$$

Variance

$$f_2 = \sum_{i=0}^{N-1} (i - f_1)^2 \, p_x(i) \qquad \text{Equation 5}$$

Normalized Variance

$$f_3 = \sum_{i=0}^{N-1} \frac{i^2}{(f_1^2 - 1) p_x(i)} \qquad \text{Equation 6}$$

Maximum Probability

$$f_4 = Max(\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} p(i,j)) \qquad \text{Equation 7}$$

Angular Second Moment

$$f_5 = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} p(i,j)^2 \qquad \text{Equation 8}$$

Entropy

$$f_6 = -\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} p(i,j) * \ln(p(i,j)) \qquad \text{Equation 9}$$

Elementary Difference 2nd Order Moment

$$f_7 = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i-j)^2 * p(i,j) \qquad \text{Equation 10}$$

Correlation

$$f_8 = \frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i*j)*p(i,j) - f_1^{\ 2}}{f_2} \qquad \text{Equation 11}$$

Product Moment

$$f_9 = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i-f_1)*(j-f_1)*p(i,j) \qquad \text{Equation 12}$$

Inverse Difference Moment (2[nd] order)

$$f_{10} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{p(i,j)}{1+(i-j)^2} \qquad \text{Equation 13}$$

METHODS AND MATERIALS

Two Brassicaceae crop species (broccoli and cabbage), three *Brassicaceae* weeds species *Brassica napus* (oilseed rape), *Capsella bursa-pastoris* (shepherd's purse) and *Raphanus raphanistrum* (wild radish), one *Caryophyllaceae* weed species *Stellaria media* (chickweed) and one *Chenopodiaceae* species *Chenopodiun album* (fat hen) were used in the study. Plants were grown in a phytotron growth chamber under similar environmental conditions (15 ^{o}C, 12 hrs of daylight provided by tungsten and fluorescent lights) and feeding regime (5 drops of bio food per ½ pint of water). All seeds were germinated in the dark. Seedlings were transplanted into growing pots once roots system has developed.

Imaging of leaves commenced at the four-leaf stage or a week to two weeks after potting. The cotyledon leaves were not considered since they all looked the same. For imaging, a leaf was surgically removed from the plant and place on a light box and an image acquired and stored, this process took just a few seconds so the leaf was still turgid. Three leaves were harvested from each plant before it was discarded. It took about a week for a leaf that could be imaged to develop which meant that the useful life of each plant was on average about three weeks.

A CCD monochrome camera with a resolution of 768 x 512 pixels was used to capture leaf images. Image capture was carried out in a dark room and the scene was artificially illuminated. Lighting intensity and image resolution were kept constant for all experiments by marking the camera setting and also having a calibration image. Individual leaves were placed flat on the light box. The light box was positioned normal to the axial plane of the camera. The orientation of the leaves on the light box was random, that is the tip of a leaf can either be North, South, West, East or at any direction. The light box was powered with two fluorescent tubes (35 W) and the diffuser (translucent Perspex) was 3 mm thick.

Images were grabbed using PC Image software (Foster Findlay, Newcastle, UK) with a Sprynt 40 MHz I860 frame grabber (Synoptics Ltd, Cambridge, UK) running on a 133 MHz Pentium. All images were stored in TIFF file format. Image processing routines were written in C on UNIX platform multi-user Sun Enterprise 3000 with 1 GB of memory and six 250 MHz Ultra Spark II processors.

Texture features of leaves were expressed in the form of feature vectors comprising ten (10) textural parameters extracted from the 255 x 255 (note: 0 to 254 gray levels) co-occurrence matrix; the 255 gray level was threshold as background. The ten textural parameters calculated ($f_1, ..., f_{10}$) are the elementary difference 2nd order moment (EDM2), product moment (PM), maximum probability, inverse difference moment (IDM), entropy, correlation, angular second moment (ASM), mean, variance and normalized variance.

TEXTURE CLASSIFICATION METHOD

Bayesian classification was used to classify leaves of different species on the basis of texture. The average textural feature vectors for a number of leaves of different species were input to a numerical Bayesian classifier and classification was based on minimum Mahalanobis distance between a mean feature vector determined from a training set and the test set feature vector (Brown et al. 1988). A case was assigned to the class with the highest probability using equation 14 below.

$$p_{ij} = \frac{e^{(S_{ij})}}{\sum_{k=0}^{G-1} e^{(S_{ik})}} \qquad \text{Equation 14}$$

Where

P_{ij} posterior probability that case *i* belongs to *j*

G number of groups or classes

S_{ij} classification score of *i* th case from the *j* th group.

Using the average feature vector as input to the classifier guaranteed invariance under rotation. Step-wise discrimination was used to reduce the number of parameters in the feature vector while ensuring that the accuracy of classification was not significantly lowered. Out of ten textural parameters calculated, only seven ($f_{10}, f_6, f_8, f_7, f_5, f_1, f_3$) were selected as significant classification parameters as shown in Table 1, this was based on the F-statistic values.

Table 1. Statistical Summary Table.

Variable	U-Statistic	F-Statistic
Inverse difference moment	0.2960	58.667
Entropy	0.1245	44.939
Correlation	0.0499	43.316
Elementary difference moment	0.0241	40.372
Angular second moment	0.0153	35.493
Mean	0.0089	27.682
Normalized variance	0.0073	25.001

RESULTS

The AOI method was tested on fat hen and charlock leaves images. In supervised mode the percentage classification of test leaves was 85% but this reduced to 63% in unsupervised mode showing the degrading effect of textural artifacts caused by inclusion of AOIs containing leaf edge outlines and strong veins Figure 4. This result suggested that if texture analysis is to be applied to leaf images then a more robust alternative approach was required. A total of 272 (training + test data) AOIs were used.

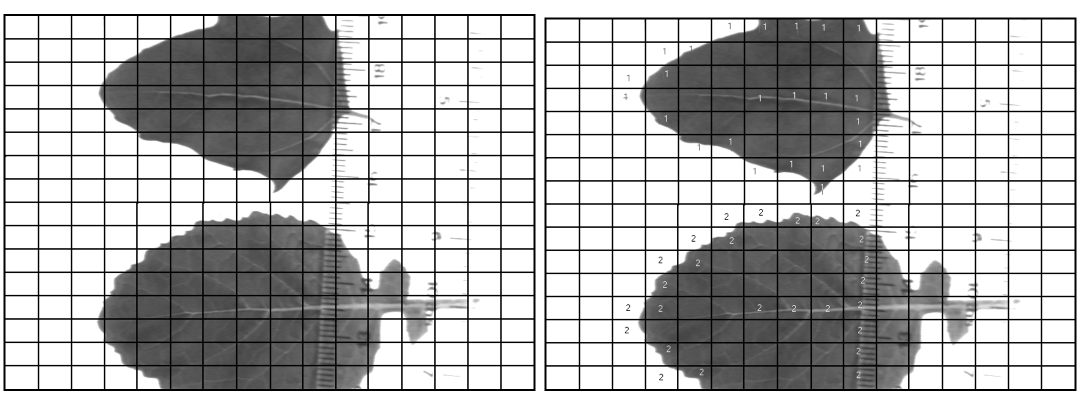


Figure 4. Image of fat hen and charlock leaves showing grid of AOIs. Labeled AOIs are those excluded from the supervised classification.

The Whole leaf method was tested on all plant species. The resulting classifications are presented in the form of contingency tables showing the numbers correctly classified (on the diagonal) and the numbers misclassified as another leaf type. Table 2 shows the results for classification of all plant species, i.e. including both crop species. The percentage classification is above 70% for all species with the highest being shepherd's purse of which 93% were correctly classified. The percentage classification for cabbage and broccoli was low due to their being misclassified as each other.

Table 2. Contingency Table for Broccoli, Cabbage and 5 weed plants.

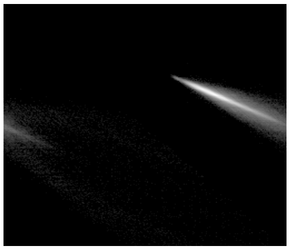
	A	**B**	**C**	**D**	**E**	**F**	**G**	**%**
A	36	8	0	0	0	0	0	82*
B	14	34	0	1	0	0	0	71*
C	0	0	33	0	0	4	0	89
D	0	2	1	34	0	0	1	89
E	0	0	0	1	47	7	1	84
F	0	0	1	0	1	40	1	93
G	0	0	0	9	1	2	32	73

key: A-Broccoli, B-Cabbage, C-Chickweed, D-Oilseed rape, E-Fat-hen, F-Shepard's purse and G-Wild radish.

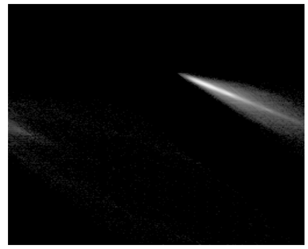
A further classification of one crop with all the weeds improved the percentage classification of crop to 98% for cabbage and to 100% for broccoli. It is also interesting to note the high percentage discrimination between Brassica species, which were not more noticeably misclassified as each other, than other species. The resolution of all the test and training images was 2234 pixels/cm2 and a total of 311 single leaf images were used to test (trial group) the classifier.

Figure 5 below show the visualization of the Co - occurrence matrices of the different images, the entries have been normalized with the highest number of entries and represented in 256 gray levels.

The Haley's comment like trace is apparent showing the diagonally of the matrices, and as expected the broccoli and cabbage plant leaves traces are similar.



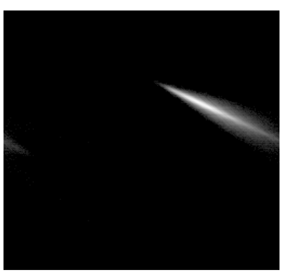
Broccoli



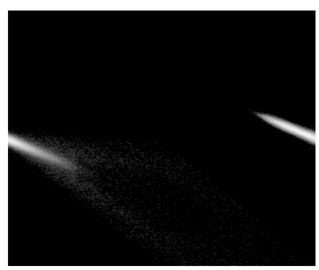
Cabbage

Chickweed

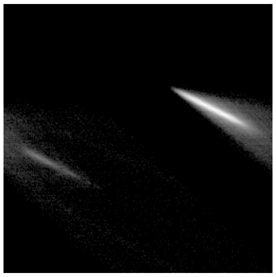
Fathen



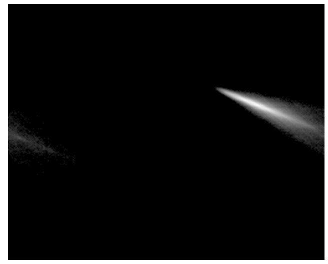
Oilseed rape



Shepherds purse



Wild radish



Charlock

Figure 5. Images of the Co - occurrence Matrices of the Plants.

Conclusions

This study provides evidence that texture based discrimination can be successfully applied to discrimination of cabbage and broccoli from a range of weeds. A minimum discrimination level of 90% or better, which is the result of grouped weeds versus cabbage and broccoli, is probably necessary in practice. Further work is required to assess the effect of leaf orientation on the quality of separation using texture and to determine the potential for plant canopy discrimination. It is noted that the simplification made by capturing an image of a single leaf was needed in order to asses the viability of this approach and in future, the results from this experiment will be used to try and segment leaves from a plant canopy or for plant species identification and classification.

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