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Texture as the basis for individual tree identification

Ashok Samal [a,*], James R. Brandle [b], Dongsheng Zhang [a]

[a] *Department of Computer Science and Engineering, University of Nebraska, 115 Ferguson Hall, Lincoln, NE 68588-0115, USA*
[b] *School of Natural Resources Science, University of Nebraska, Lincoln, NE 68588-0115, USA*

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Abstract

Recognizing plants from imagery is a complex task due to their irregular nature. In this research, three tree species, Japanese yew (*Taxus cuspidata* Sieb. & Zucc.), Hicks yew (*Taxus x media*), and eastern white pine (*Pinus strobus* L.), were identified using their textural properties. First, the plants were separated from their backgrounds in digital images based on a combination of textural features. Textural feature values for energy, local homogeneity, and inertia were derived from the co-occurrence matrix and differed significantly between the trees and their backgrounds. Subsequently, these features were used to construct the feature space where the nearest-neighbor method was applied to discriminate trees from their backgrounds. The recognition rates for Japanese yew, Hicks yew, and eastern white pine were 87%, 93%, and 93%, respectively. The study demonstrates that the texture features selected and the methods employed satisfactorily separated the trees from their relatively complex backgrounds and effectively differentiated between the three species. This research can lead to potentially useful applications in forestry and related disciplines.

* Corresponding author. Tel.: +1 402 472 2217; fax: +1 402 472 7767.
E-mail address: samal@cse.unl.edu (A. Samal).

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1. Introduction

Recognition of objects is a central and one of the most difficult tasks in computer vision [2,16]. Furthermore, identification of natural objects such as plants is even more complex [7,13,14]. The primary reason for this is the fact that a given object (say a plant) does not have a fixed shape. Multiple instances of a given species of a plant are similar in some core aspects, but a simple template matching will not be adequate in most cases [13]. A variety of approaches have been used to recognize objects in general [1,11,16,18] with varying amount of success in different domains. In biological studies, shape attributes have been extensively used in plant identification [3,19]. A combination of size, shape, and location data were successfully used in recognizing plants [17]. Optical or spectral properties of plants in digital images have also been used for isolation of plants from their backgrounds [4,10]. Gougeon and Leckie have extensively studied the problems of identification of tree crown of individual species from high resolution satellite images [6,5]. In this research we explore the identification of tree species using frontal views. This will also have many applications in forestry [5]. Sensor networks of various kinds have been proposed in many different applications. It is now conceivable to have a network of sensors (cameras) at remote sites to monitor the growth of plants or trees. It is therefore important to develop a good understanding of the effectiveness of machine vision techniques in different applications. Fig. 1 shows some sample trees for three different species.

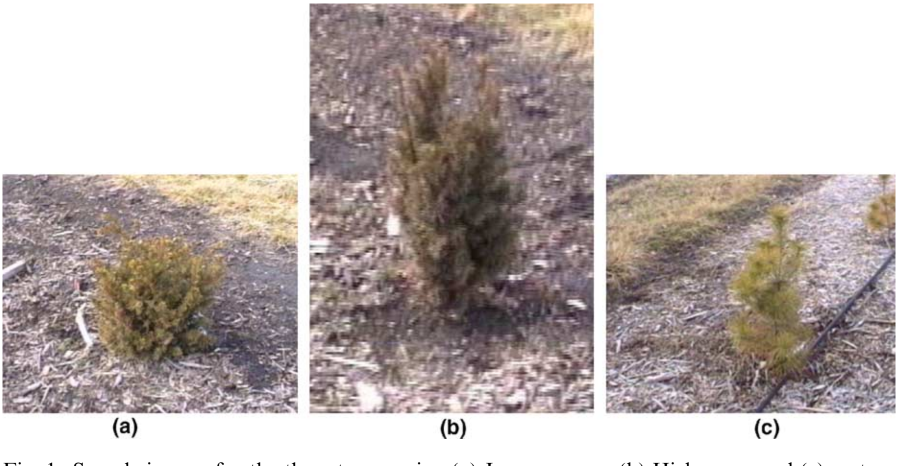

Fig. 1. Sample images for the three tree species. (a) Japanese yew, (b) Hicks yew, and (c) eastern white pine.

One critical issue that must be considered is that shape features and optical properties of plants vary with the stage of growth [17,19], and the light conditions [4] when the images are taken. According to [12], textural analysis is possible on both statistical and structural levels. In this study, several texture features were derived from the co-occurrence matrix of grayscale images, because these features do not suffer from the limitations associated with the shape and optical properties of plants. Statistical analysis of these texture features was performed, and the features that showed significant differences between trees and their backgrounds were selected for texture segmentation and tree identification.

2. Materials and methods

2.1. Study site and tree species

Three tree species, Japanese yew (*Taxus cuspidata* Sieb. & Zucc.), Hicks yew (*T. x media*), and eastern white pine (*Pinus strobus* L.), were grown at the Landscape Services Nursery at the University of Nebraska, Lincoln. Trees were 5- to 8-years-old and 0.5–1 m tall at the time of the study. Background material was a combination of wood chips, grass and trees.

2.2. Image acquisition and preprocessing

Seventy five (75) color color images of trees growing in the field were recorded using a Sony Video Camera Recorder (Model No. CCD-V5000). Images of 25 different trees for each species were transferred to a captured into a UNIX SUN SPARC station in the Computer Vision and Image Processing Laboratory of Computer Science Department at the University of Nebraska, Lincoln. Finally the 24 bit true color images were converted to 8 bit grayscale images. In this study, histogram equalization was used to enhance the degree of contrast between the different features.

There are several reasons for using grayscale images instead of color. Using color images means larger amount of data resulting in longer computation times. More significantly, use of color for trees of same or similar species does not significantly help in classification. The three species considered here have vary similar color profile. Furthermore, depending on the growth, moisture availability would change the "greenness" of the leafy part of the plant and would further complicate the use of color.

2.3. Feature extraction

Feature extraction was used to extract relevant features from the images resulting in quantitative information for each tree. The approach employed in this study was to use statistical texture analysis to determine a set of measures to provide object-background as well as object–object discrimination. The gray level spatial dependence approach characterizes texture by the co-occurrence of its gray levels [8]. The definition and construction of the co-occurrence matrix are documented in many text books including the work by [11]. The co-occurrence matrices are derived from the grayscale version of the original 24 bit true color image. The co-occurrence matrices are computed for each window (region or token) around each pixel over the images both in training and testing steps. Window size can be determined by the user, and was chosen as 5 by 5 pixels.

The co-occurrence matrix is a second order statistic that measures gray level variation in an image. It indicates the joint probability of gray level occurrence at a certain displacement (distance and angle) in an image.

Given a displacement (d) and angle (θ), the co-occurrence matrix is given by

$$C_{d,\theta}[i,j] = |\{[r,c]|I[r,c] = i \wedge I[r + d\cos(\theta), c + d\sin(\theta)] = j\}|$$

where $I[r,c]$ is the intensity at the image at location (r,c). A normalized co-occurrence matrix, $N_{d,\theta}$, is derived from the above matrix by dividing each element by the sum of all the values in the matrix.

The choice of 5×5 window is based on several factors. A larger window size would result in longer computation time without necessarily improving the results. The goal is to extract the texture information by analyzing the relationships between the neighboring pixels. Our experiments showed that window of this size achieves a good balance between the two competing needs (computational efficiency and effectiveness). While scale does play a role in texture, in this case, this window size should still be effective for images at different resolutions as well.

The co-occurrence matrix is then normalized [10] and texture features such as energy, local homogeneity, and inertia are derived from it. These features are widely used in literature [11,16] and have proven to be effective in similar applications [10]. The selection of these features is also motivated by careful observations of the images.

Given the co-occurrence matrix, we can compute the three texture parameters used in this research as follows:

$$\text{Energy} = \sum_i \sum_j N^2_{d,\theta}[i,j]$$

$$\text{Local homogeneity} = \sum_i \sum_j \frac{N_{d,\theta}[i,j]}{1 + (i-j)^2}$$

$$\text{Inertia} = \sum_i \sum_j (i-j)^2 N_{d,\theta}[i,j]$$

2.4. Training process

Manual training is used in this study. Three sets of images are used for the three tree species. Each set consisted of 10 grayscale images. Each image in the training set was manually separated into background and tree subimages. The feature values are then computed for each point in the two subimages using a 5×5 window. The average values for each feature is computed for the background and the tree subimage. One way analysis of variance (ANOVA) was used to arrange the data. In the statistical analysis, two treatments, namely, *background* and *tree*, were considered. The difference in feature values between two treatments for each type of plant images was tested using the General Linear Model (GLM) of SAS [15]. The features that were significantly different statistically (as determined by the GLM model) between the tree part and background were used to construct the feature space. Finally the standard feature values of both backgrounds and tree parts in each training set were calculated as the mean of the corresponding values computed from all the images in that training set.

2.5. Testing process

For each tree species, the test set consisted of 15 grayscale images of different trees (not used for training). The testing process consisted of two steps: texture segmentation and tree identification.

Texture segmentation: For each test image, the values of the selected features were calculated based on the normalized co-occurrence matrix for each 5 by 5 window. Given the standard feature values obtained in the training process, the simple Euclidean distance [11] to the given background and tree part were calculated in the feature space. The pixel was then classified as either background or tree part using nearest-neighbor classification method. If the pixel was classified as background, the pixel value was set to 255 (background).

Tree identification: After texture segmentation, some background parts may be misclassified as tree parts, and some tree parts may be misclassified as background parts. The goal of the next step was to correct the misclassified areas or regions. The Blob Coloring algorithm was employed to compute the connected components [11,16]. This is a two-pass algorithm that assign a label (or region number) to each pixel based on a small local neighborhood around the pixel. Assuming that the largest connected component corresponds to a tree part in a digital image, the other connected components therefore correspond to the background part, and the values of all the pixels within those regions are assigned to be the background. The assumption that the largest connected component corresponds to the tree part in a digital image is reasonable and holds true in most of the cases. If the tree part is not the dominant part in the original image, the image can to be cropped to meet this assumption. To correct the misclassified tree parts which result in holes in a tree crown, the Blob Coloring algorithm was applied again to the image whose background had been corrected.

At this point, we have a large blob corresponding to the tree crown and a set of smaller blobs inside this that are classified as background. Many of these smaller blobs are insignificant and can be eliminated using simple morphological operations. The erosion algorithm [9,16] was then applied to the regions or connected components which had been classified as background in the tree part. The optimal number of erosion steps was empirically determined during the training process. The optimal number of erosion steps for Japanese yew, Hicks yew, and eastern white pine were determined to be 4, 8, and 8, respectively. During the sequence of erosion steps, the size of each region within the tree part that had been classified as background became smaller and smal-

Table 1
Mean feature values

Tree species	Features	Feature values (SE)	
		Tree	Background
Japanese yew	Energy	0.046(0.004)	0.035(0.001)
	Local homogeneity	0.212(0.006)	0.164(0.005)
	Inertia	31.068(1.589)	56.828(1.856)
Hicks yew	Energy	0.043(0.001)	0.030(0.001)
	Local homogeneity	0.231(0.008)	0.135(0.002)
	Inertia	28.243(1.734)	64.702(1.658)
Eastern white pine	Energy	0.045(0.002)	0.032(0.001)
	Local homogeneity	0.246(0.010)	0.141(0.004)
	Inertia	24.938(2.243)	61.651(0.889)

Table 2
Output from general linear models (ANOVA) for testing the difference in feature values between tree parts and backgrounds

Tree species	Dependent variable	Degrees of freedom	Mean square	*F*-value	Probability value
Japanese yew	Energy	1	0.0004966	6.51	0.0213
	Local fomogeneity	1	0.0104710	33.73	0.0001
	Inertia	1	2986.3310	111.18	0.0001
Hicks yew	Energy	1	0.0007401	67.25	0.0001
	Local homogeneity	1	0.0418870	114.93	0.0001
	Inertia	1	5981.5660	230.82	0.0001
Eastern white pine	Energy	1	0.0007686	23.79	0.0002
	Local homogeneity	1	0.0495598	87.35	0.0001
	Inertia	1	6065.3874	231.47	0.0001

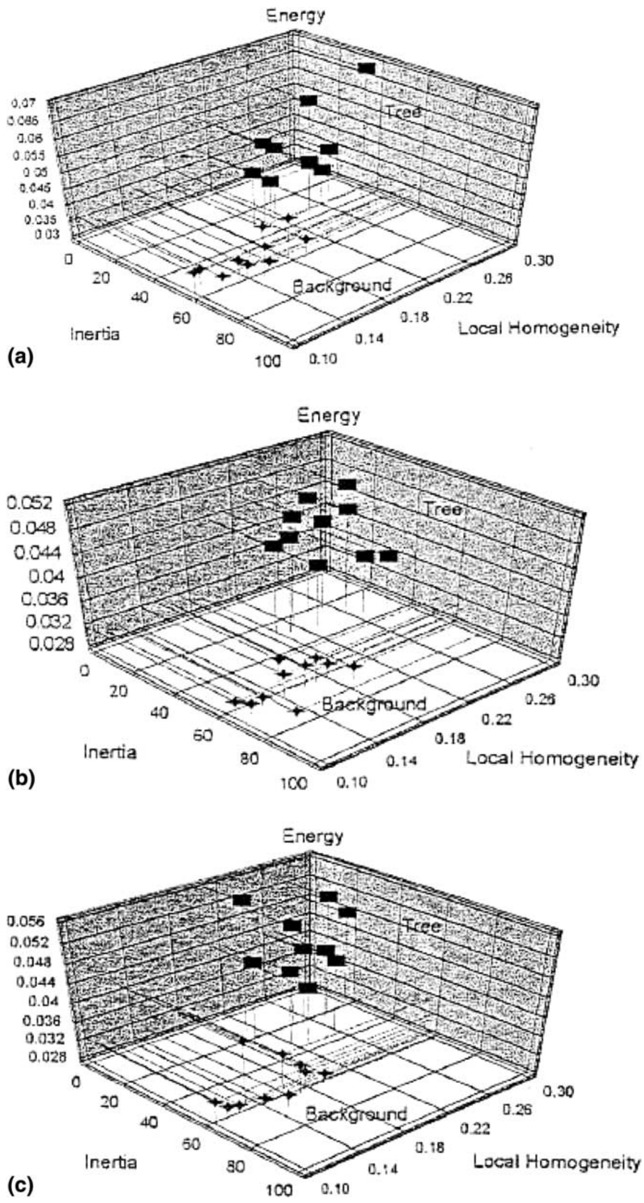

Fig. 2. Separation of tree and background in the texture feature space. (a) Japanese yew, (b) Hicks yew, and (c) eastern white pine.

ler, and at each step, some of the regions in the tree part of the image would be closed. Those regions that were not closed up at the final step were determined as holes. It should be noted that this number can either be determined experimentally for each species as we have done or set to a reasonable number that is constant across all species of similar structure. In our case using 6 or 8 steps in all three types of species yielded very similar results.

3. Results and discussions

3.1. Statistical texture analysis

The mean feature values of both tree parts and backgrounds for each tree species are shown in Table 1. The results from the one-way variance analysis of the GLM model indicated the difference in mean value of each feature is statistically significant between tree part and background (Table 2). Consequently three texture features, energy, local homogeneity, and inertia, were used to construct the feature space where the texture was segmented using the nearest-neighbor method [11,16]. Based on the feature values computed from the training images in each training set, there are two distinguishable clusters in feature space, namely tree and background (see Fig. 2).

3.2. Texture segmentation, tree identification, and testing results

Figs. 3–5 show the sequence of processing steps for the three tree species shown in Fig. 1. Figs. 3(a), 4(a), 5(a) show the gray scale images for the three

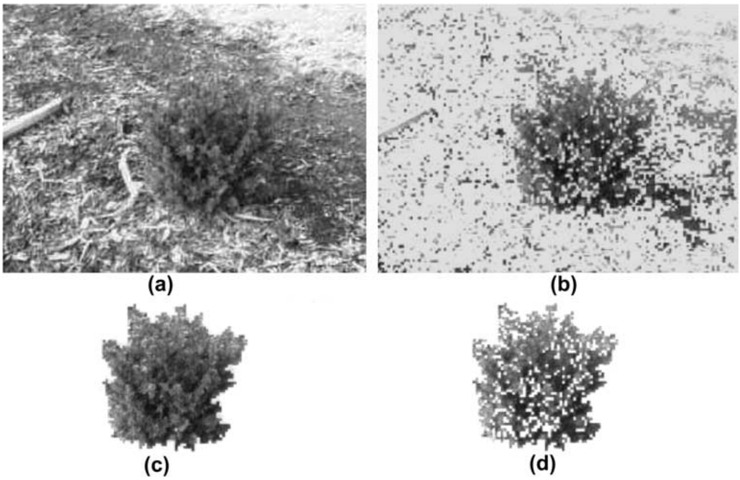

Fig. 3. Processing stages for a sample tree (Japanese yew). (a) Original image (grayscale), (b) after texture segmentation, (c) after connected components analysis, and (d) after morphological operations.

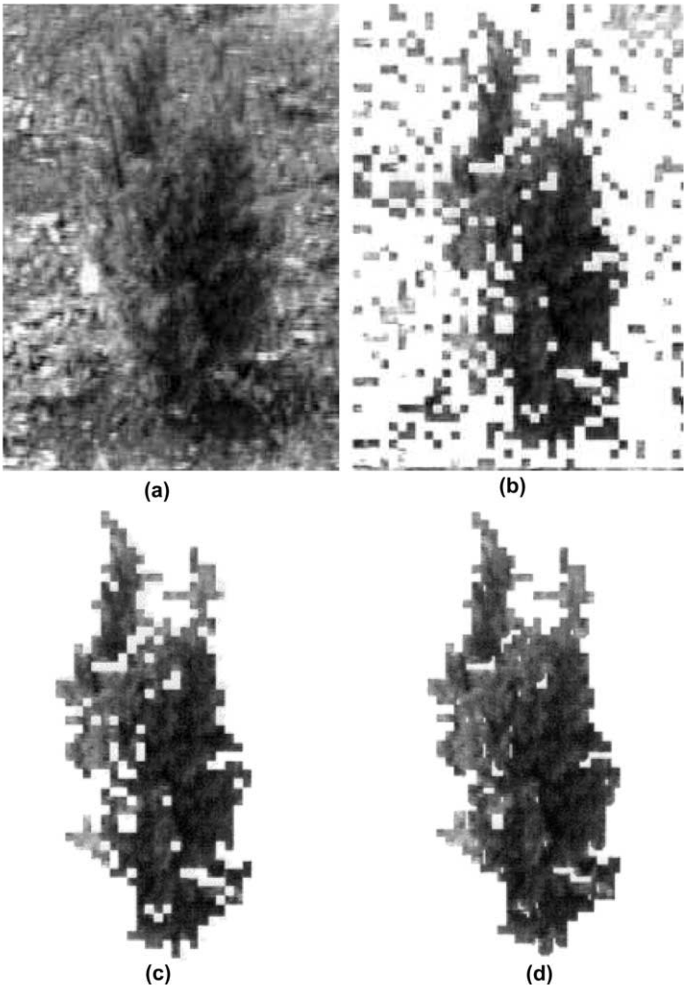

Fig. 4. Processing stages for a sample tree (Hicks yew). (a) Original image (grayscale), (b) after texture segmentation, (c) after connected components analysis, and (d) after morphological operations.

trees. After texture segmentation, the resulting images are shown in Figs. 3(b), 4(b), 5(b). Clearly there are some small regions that have been misclassified, but in general the tree parts are recognized based on the texture features. By applying the Blob Coloring algorithm, the misclassified background parts were corrected under the assumption that the largest connected component corresponds to the tree part in the original image (Figs. 3(c), 4(c), 5(c)). After applying Blob Coloring algorithm again, and the Erosion algorithm to the images whose

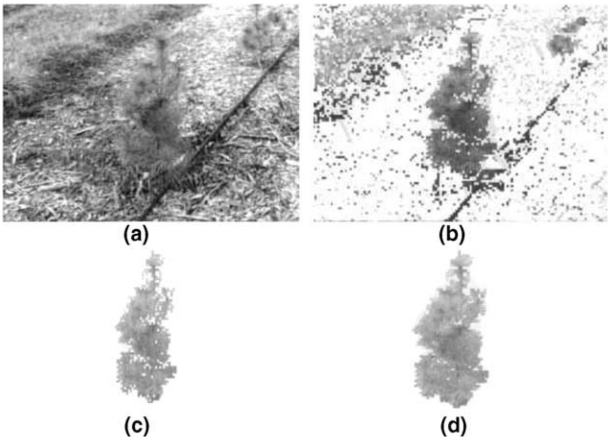

Fig. 5. Processing stages for a sample tree (eastern white pine). (a) Original image (grayscale), (b) after texture segmentation, (c) after connected components analysis, and (d) after morphological operations.

Table 3
Testing results

Tree Species	Number of images in each testing set	Number of images with trees being recognized	Recognition rate (%)
Japanese yew	15	13	87
Hicks yew	15	14	93
Eastern white pine	15	14	93

backgrounds had been corrected, the misclassified tree parts were corrected and the holes within the tree parts were determined given a number of steps for erosion (Figs. 3(d), 4(d), 5(d)). The recognition rates of trees were determined by visually comparing the resulting images with the original images. If the resulting image was representative of the original image, including tree crown outline and holes within tree crown, it would be classified as recognized. If there is a visual error in determining tree outline or holes, it would be classified as unrecognized. The overall testing results are shown in Table 3. In general, the texture features selected and methods employed worked satisfactorily in separating trees from their backgrounds and in their classification.

4. Conclusions

The most important facts that can be concluded from this study are: texture features, energy, local homogeneity, and inertia, derived from co-occurrence matrices can successfully discriminate some evergreen plants and a relatively complex background. Co-occurrence statistics offer ease of computation in addition to reliability. Texture features derived from co-occurrence matrix may be more reliable than spectral properties in some cases because of their non-dependence on lighting conditions. A combination of different features may perform better in separating tree parts from a relatively complex background in feature space.

Identification of trees from imagery has many practical applications. Inventories of trees in urban landscapes can be made both efficiently and inexpensively using this method. Once trees are identified, volume estimate of trunk and branches, which are proportional to the amount of biomass can be computed. This is an approximate, but quick estimate of the amount of carbon sequestration. To determine the best use and practical implications of classification, further studies are needed in this area.

References

[1] D. Ballard, C. Brown, Computer Vision, first ed., Prentice-Hall, Inc., NJ, 1985, p. 523.
[2] D. Forsyth, J. Ponce, Computer Vision—A Modern Approach, Prentice Hall, 2003.
[3] E. Franz, M.R. Gebhardt, K.B. Unklesbay, Shape description of completely visible and partially occluded leaves for identifying plants in digital images, Transactions of the ASAE 34 (2) (1991) 673–681.
[4] E. Franz, M.R. Gebhardt, K.B. Unklesbay, The use of local spectral properties of leaves as an aid for identifying weed seedlings in digital images, Transactions of the ASAE 34 (2) (1991) 682–687.
[5] F. Gougeon, D.G. Leckie, Forest information extraction from high spatial resolution images using an individual Tree Crown Approach, Information Report BC-C-396, Natural Resources Canada, 2003. Available from: <http://warehouse.pfc.forestry.ca/pfc/21272.pdf>.
[6] F. Gougeon, D.G. Leckie, Individual Tree Crown analysis: a step towards precision forestry, in: Proceedings of the First International Precision Forestry Symposium, June 17–20, 2001.
[7] D.J. Holliday, A. Samal, Object recognition using L-system fractals, Pattern Recognition Letters 16 (1995) 33–42.
[8] R.M. Haralick, Statistical and structural approaches to texture, in: Proceedings of Fourth International Joint Conference on Pattern Recognition, Kyoto, 1978, pp. 45–49.
[9] R. Jain, R. Kasturi, B. Schunck, Machine Vision, McGraw-Hill, New York, 1995, 549 p.
[10] G.E. Meyer, T. Mehta, M.F. Kocher, D.A. Mortensen, A. Samal, Textural imaging and discriminant analysis for distinguishing weeds for spot spraying, Transactions of the ASAE 41 (4) (1998) 1189–1197.
[11] M.E. Nadler, R.P. Smith, Pattern Recognition Engineering, John Wiley & Sons Inc., NY, 1994, 608 p.
[12] A. Rosenfeld, B.C. Lipkin, Texture synthesis, in: B.C. Lipkin, A. Rosenfeld (Eds.), Picture Processing and Psychopictorics, Academic Press, New York, 1970, pp. 562–569.
[13] A. Samal, J. Edwards, Generalized Hough transform for natural shapes, Pattern Recognition Letters 18 (1997) 473–480.
[14] A. Samal, B. Peterson, D.H. Holliday, Recognizing plants using stochastic L-systems, Journal of Electronic Imaging 11 (1) (2002) 50–58.
[15] N.C. Carry, SAS User's Guide: Statistics Ver.5, SAS Institute Inc., 1985, pp. 60–70.

[16] L.G. Shapiro, G.C. Stockman, Computer Vision, Prentice Hall, New York, 2001, 580 p.
[17] W. Simoton, J. Pease, Automatic plant feature identification on Geranium cuttings using machine vision, American Society of Agricultural Engineerings 33 (6) (1990) 2067–2073.
[18] M. Sonka, V. Hlavac, R. Boyle, Image Processing, Analysis, and Machine Vision, Brooks/Cole Publishing Co., Pacific Grove, CA, 1999, 770 p.
[19] D.M. Woebbecke, G.E. Meyer, K. VonBargen, D.A. Mortensen, Optical and color separation of broadleaf weeds and grasses from various backgrounds for spot spraying applications, Transactions of the ASAE 38 (1) (1993) 259–269.