Weed recognition in corn fields using back-propagation neural network models

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[1]*Department of Agricultural and Biosystems Engineering, Macdonald Campus of McGill University, Ste-Anne-de-Bellevue, Québec, Canada H9X 3V9; and* [2]*Département de génie de la production automatisée, École de technologie supérieure, Montréal, Québec, Canada H3C 1K3.*

Yang, C.-C., Prasher, S.O. and Landry, J.A. 2002. **Weed recognition in corn fields using back-propagation neural network models**. Canadian Biosystems Engineering/Le génie des biosystèmes au Canada **44**: 7.15-7.22. The objective of this study was to develop back-propagation artificial neural network (ANN) models to distinguish young corn plants from weeds. Digital images were taken in the field under various natural lighting conditions. The images were cropped and resized to smaller sub-images containing either corn plants or weeds. The green objects in the images were extracted with the greenness method, thus counting the pixels with a green intensity larger than red and blue intensities and replacing other background pixels with the intensity of zero. The extracted colour images were then converted to intensity images to save computational efforts during the ANN model development. The number of images available for training was quadrupled by rotating counter-clockwise each image by 90, 180, and 270 degrees. Several hundred images of corn plants and weeds were used for training the model. The ability of the ANN models to discriminate weeds from corn was tested. The highest success recognition rate was for corn at 100%, followed respectively by *Abutilon theophrasti* at 92%, *Chenopodium album* at about 62% and *Cyperus esculentus* at 80%. The ANN model required less than one minute to process 250 images containing 80x80 pixels. The inability of ANN models to properly classify weeds and corn plants was due to our inability to use a greater number of processing elements in the formulation of the ANN models. This was most likely caused by issues related to PC memory management. **Keywords:** neural networks, image recognition, image processing, greenness, precision farming.

L'objectif de cette étude fut de créer un modèle à l aide d un réseau neuronal dont l entraînement est fait par rétro-propagation pour faire la distinction entre des plants de maïs et des mauvaises herbes. Des images numériques furent prises au champ sous divers éclairages naturels. Les images furent découpées et redimensionnées en sous-images contenant soit des plants de maïs ou des mauvaises herbes. Les objets verts de l'image furent extraits en comptant les pixels ayant une intensité supérieure en vert comparativement au rouge et au bleu, et en attribuant une intensité de zéro aux autres pixels d arrière-plan. Les images en couleur furent converties en images monochromes afin d écourter le calcul informatique lors du développement du réseau neuronal. Le nombre d'images fut quadruplé en tournant l image dans le sens anti-horaire par 90, 180, et 270 degrés. Des centaines d'images de plants de maïs et de mauvaises herbes furent utilisées pour l'entraînement du modèle. La capacité des modèles à distinguer les mauvaises herbes des plants de maïs fut examinée. Le taux de reconnaissance fut de 100% pour le maïs, de 92% pour l *Abutilon theophrasti*, de 62% pour le *Chenopodium album*, et de 80% pour le *Cyperus esculentus*. Le modèle a pris moins d une minute pour gérer 250 images de 80 par 80 pixels. L'incapacité des modèles à classer les mauvaises herbes et les plants de maïs fut attribuée à notre incapacité à utiliser un plus grand nombre de neurones dans la formation des modèles. Ceci est probablement attribuable aux complications occasionnées dans la gestion de la mémoire interne de l ordinateur.

INTRODUCTION

One approach to reducing the quantities of herbicide used in agricultural production is to apply them only where they are needed rather than uniformly over the field or crop row. Although the weed detection, status assessment, decision, and control functions required by a precision herbicide application system can be performed by a human operator, such tasks can, in principle, be performed more efficiently by an automated system (Schueller and Wang 1994). Machine vision can be used to gather information while the vehicle pulling the herbicide sprayer is in motion. This information can be processed, analysed, and transformed into inputs for a decisional algorithm that controls the sprayer nozzle action in real-time. Which criteria are to be used by the decision module and how the temporal requirements will be met for real-time functioning are problems yet to be resolved.

The economic threshold is one possible criterion. It was defined as the weed density at which the cost of control equals the predicted crop yield loss if the weed is not controlled (Lindquist et al. 1999). Vangessel et al. (1995) noted that the yield-loss equation in WEEDCAM, a corn-weed management model, involves the total competitive value of all weeds present in a field. The total competitive value of a given species is the product of the number of individual plants and the competitiveness index (CI) for that species. The CI must be determined beforehand, either experimentally or by surveying the opinion of farmers (Hartzler 1997) or other experienced people involved in agricultural production (consultants, input salespersons, etc.). If these concepts are to be applied in the decisional module of the precision spraying system, it is clear that the image analysis and interpretation routines should be able to distinguish between weed species and differentiate them from the crop species. If this level of performance is not possible or not desired, the decisional routine could be based on an average economic threshold involving the most common weed species. This would demand a simpler not-crop/crop differentiation from the image analysis module. The simplest possibility is a yes/no decision for herbicide application based on a preset threshold for weed density that could be based on the operator’s or the farmer‘s perception of weed threat to a given crop.

Object differentiation is the most complex of the tasks to be performed by the system and should therefore require the greatest computational effort. Some algorithms have been developed to identify weeds using machine vision (Yonekawa et al. 1996; Meyer et al. 1998; Hemming and Rath 2001). Artificial neural networks (ANNs) might be useful in lowering the requirement in computer resources for object differentiation if they can be successfully trained. ANNs of various architectures have been used to perform image recognition for classifying plant species (Burks et al. 2000; El-Faki et al. 2000; Oide and Ninomiya 2000). They were developed by using optimal discriminant parameters as inputs to the ANNs chosen using techniques such as divergence feature selection, discriminant analysis, principal components, and others. Although these methods result in small ANN structures, these procedures require further computational time and effort. It is not clear whether devoting preprocessing time to arrive at a small ANN structure with high classification success is advantageous compared to the alternative, which is to eliminate preprocessing but use an ANN with a much larger structure. The answer to this problem depends on the level of classification success one can attain with a larger ANN structure using information in which the discriminating information is still only implicit. It also depends on the comparative execution times from image collection to sprayer action.

Thus, this study was aimed at evaluating the possibility of developing ANNs to satisfy the object recognition requirements of precision herbicide application, without depending on an optimized parameter set. Images of corn and weed plants were taken in fields in southwestern Quebec under natural light and weather conditions, to serve as training and testing material for ANN development. The weed species included in this study were velvetleaf (*Abutilon theophrasti* Medic.), quack grass (*Agropyron repens* (L.) Beauv.), lamb's-quarters (*Chenopodium album* L.), and yellow nut sedge (*Cyperus esculentus* L.). Two recognition (classification) problems were attempted as objectives. The first objective required that the ANN classify plants as corn or not-corn (i.e., weed). This ability should be sufficient in fields that have one predominant weed competitor or weeds with similar competitive indices. The second objective required that specific weeds be recognized. An ANN with this ability would clearly be applicable to a wider range of environments.

MATERIALS and METHODS

The digital colour images used for this study were taken from random locations on three corn fields, #18, #22, and #24 of Macdonald Campus Experimental farm of McGill University in Ste-Anne-de-Bellevue, southwestern Quebec. Field #18 was 3 ha, field #22 was 11.7 ha, and field #24 was 8.5 ha. Prior to planting, all fields were tilled to kill any weeds. Images were taken from field #18 on May 21, 25, 26, 29, and 30, from field #22 on May 20, 23, and 27, and from field #24 on May 19, 22, and 28 of 1998, when corn plants were at the five- or six-leaf stage. Four of the most common weed species found from the images in these fields were *Abutilon theophrasti*, *Agropyron repens*, *Chenopodium album*, and *Cyperus esculentus*. These weed species were collectively used as the objects to be differentiated from corn.

Equipment

A Kodak DC50 digital zoom camera was used to obtain colour images of corn and weeds. The images from this camera have a resolution as high as 756x504 pixels with 24-bit millions of colours. During image collection, the camera was always held at the same height of 600 mm and perpendicular to the ground to shoot the bird-view images of objects on the ground. It was sometimes necessary to slightly zoom in or zoom out to obtain images clear enough for unaided human eyes to recognize any green objects. Although the actual size covered by an image varied slightly from image to image, the covered area was kept at approximately 300 x 200 mm.

The images were downloaded to the computer and converted from native Kodak digital camera format (KDC) to the 8-bit colour bitmap format (BMP) using PhotoEnhancer v2.1 software, ranging from 134 to 137 kB. The converted BMP files were 373 kB in size. Although the BMP format takes more space than other formats, it is widely supported by commercial graphic processing programs.

Image processing

Image processing and ANN development were carried out on a PC with a Pentium II 300 MHz processor, 4 GB of hard disk space, 128 MB of RAM, and the Windows 98 operating system. Images were processed by the Image Processing Toolbox v2.2 of MATLAB v5.3 for Windows 98, developed by MathWorks, Inc. (MathWorks 1998a, 1999). In MATLAB, an RGB format is used to read BMP images directly in a red-green-blue (RGB) colour system. Each pixel of an image contained three values, ranging from zero to one, for red, green, and blue intensities. The values of these three primary colours make up the actual colour for each pixel. Therefore, each image of 756x504 pixels is represented by a matrix of 756x504x3. Because, according to preliminary studies, this size of array was too large to be practical as an input for ANN training due to memory limitations, the images were cropped to object arrays of 100x100 pixels and then reduced to 80x80 by nearest neighbour interpolation. Cropping was done so as to leave only one object in the image, either a corn plant or a group of weeds to simplify the training procedure.

It was assumed that any pixel with an actual green colour, made of a combination of intensities of the three primary colours and appearing green to human eyes, was a part of a plant because the images were taken in a field. Thus, the greenness method, developed by Yang et al. (2000b), was applied to extract the plant objects from the whole image. The intensities of the three primary colours associated with a given pixel are compared. When the intensity of green is larger than the red and blue intensities simultaneously, the pixel is considered to be part of a plant. The colour coordinates of such pixels are preserved, and the colour coordinates for pixels not deemed green are set to black (0,0,0). The resulting image therefore preserves the green object and eliminates other object information. The three-coordinate colours of the object pixels and the (0,0,0) of the background are then converted to a one-coordinate format based on gray level. Thus, all background pixels are given a value of zero and those associated with a green object are coded as intensity in the range zero to one. This reduces the matrix dimension from 80x80x3 to simply 80x80 and reduces the memory requirements by 2/3. This method simplifies images and removes background noise. The human eye can still clearly recognize the objects when the gray level matrix is used in print or on screen.

For purposes of increasing the number of images available for training and accounting for the direction of approach, each image was rotated by 90, 180, and 270 degrees counter-clockwise. The preliminary tests indicated that the ANNs treated the quadrupled images different from each other because the outputs of ANNs to the images quadrupled from the same source were different from each other. Thus, rotated images could be used as independent images without overtraining the ANNs. There were therefore 1736 images of corn, 772 images of *Abutilon theophrasti*, 672 images of *Agropyron repens*, 752 images of *Chenopodium album*, and 1480 images of *Cyperus esculentus*. Some examples of images used in ANN training are given in Fig. 1.

ANN development

Back-propagation networks from the Neural Network Toolbox v3.0.1 of MATLAB v5.3 were used to build the ANN image recognition models (MathWorks 1998b, 1999) because this type has been successfully used in various applications (Timmermans and Hulzebosch 1996; Schmoldt et al. 1997; Yang et al. 1997, 2000a; Burks et al. 2000). The architecture of a back-propagation ANN was set at (6400, m, n). The number of processing elements (PEs) in the input layer was 6400, one for each of the intensity levels in the image pixel matrix. Similar ANN algorithms using intensities of pixels as inputs have been suggested by Skapura (1996) for video-image processing, by Kartalopoulos (1996) and Yang et al. (2000b) for image recognition, and by Kasabov (1996) for pattern recognition. The number of PEs in the hidden layer is denoted by m and was varied from 80 to 400. The number of PEs in the output layer, n, depended on the classification problem. The value of the i^{th} output, generated from the ANN, was denoted by ${}^{i}O$. The transfer function at each PE was set to the log sigmoid function. The maximum number of epochs in all cases was 1000 and the maximum acceptable sum of squared errors was set at 0.01 in all training sessions. The preliminary tests showed that, in few training cases, the training epochs approached 1000 before the sum of squared errors decreased to 0.01. Momentum factors were initially set at 0.975 and varied to as high as 0.99 and as low as 0.5.

In the first approach used, an ANN was trained to distinguish corn from a given weed species. The architecture of the ANN was (6400, 80, 2). During training, the outputs, specified for each image, were in binary format as follows: if the image was of corn, ${}^{1}O$ was set to one and ${}^{2}O$ was set to zero. For weeds, ${}^{1}O$ was set to zero and ${}^{2}O$ to one. Testing was performed by randomly selecting and presenting 50 images of corn and 50 images of the weed species in question. The images used for validation were different from the images used for training. The testing outputs ranged from zero to one, and the classification criterion was based on the relative values of the two outputs. If ${}^{1}O$ was the larger of the two, then the object was classified as corn.

The possibility of developing an ANN that could correctly classify corn and four specific weeds species was also explored. There were five outputs in this ANN instead of two, with definitions analogous to those in the previous section: i.e., the expected outputs in the training file were [1,0,0,0,0] for corn, [0,1,0,0,0] for *Abutilon theophrasti*, [0,0,1,0,0] for *Agropyron repens*, [0,0,0,1,0] for *Chenopodium album*, and [0,0,0,0,1] for *Cyperus esculentus*. The same 50 images of each plant species that were used in the previous model validation were used to test the ANN. Because this problem was several times more complex, the number of PEs in the hidden layer was varied from 80 to 400. When the images were used to validate the ANNs, each image was recognized as the plant species, corresponding to the output PE with the highest value.

It was not possible to use all available images simultaneously for ANN training in this study due to memory management limitations. Therefore, it became necessary to split the training image file into several smaller files and present them sequentially to train the ANN models. While the training file was split into three files to distinguish corn from *Cyperus esculentus* because of the large number of images available for this species, only two training files were made for the other three weed species. On the other hand, the master training file was split into five files while attempting to distinguish corn from all four weed species.

Ten-fold cross validation

A ten-fold cross validation is generally used to ensure full and thorough training of the ANN model (Weiss and Kulikowski 1991). In this study, it was attempted only for the case where the five plant species, i.e. corn plus 4 weed species, were to be recognized by the ANN model. Given the enormous computational efforts involved in ten-fold cross validation, it was decided that cross validation would be done for the other cases only if it was found that the ANN model was not getting appropriate and thorough training in the first case. In this method, the training and testing of the ANN model is repeated ten times, each time with different training and test files. For example, 50 images from each of the five plant species were randomly selected for model evaluation in the first run, and the remaining images were used for training. At the end of the run, another 50 images from each of the five plant species were selected randomly for evaluation and the remaining images were kept for training. In each validation phase, the number of training and testing images would be the same; however, they would be different in each cross validation run. The validation was done ten times, and the average success recognition rates and the corresponding standard deviations were calculated. The 90% confidence intervals (average $\pm$ 1.28 standard deviation) were also computed.

RESULTS and DISCUSSION

From Table 1, it is clear that differentiation between corn and *Abutilon theophrasti* was the most successful in this test. In cases where the other weed species involved in this study predominated, Table 1 indicated that the missclassification rate was high enough to be significant from the point of view of decision-making. The low success recognition rates for the other three weed species may have been caused by insufficient training of ANNs. In practical terms, this means that in about one-half of the area traversed by the spraying system where weeds are in fact present, the weeds would be classified as crop. This may have serious consequences if a large percentage of field area has weed populations above the economic threshold, but would be unimportant if the weed population is below its economic threshold over most of the field area.

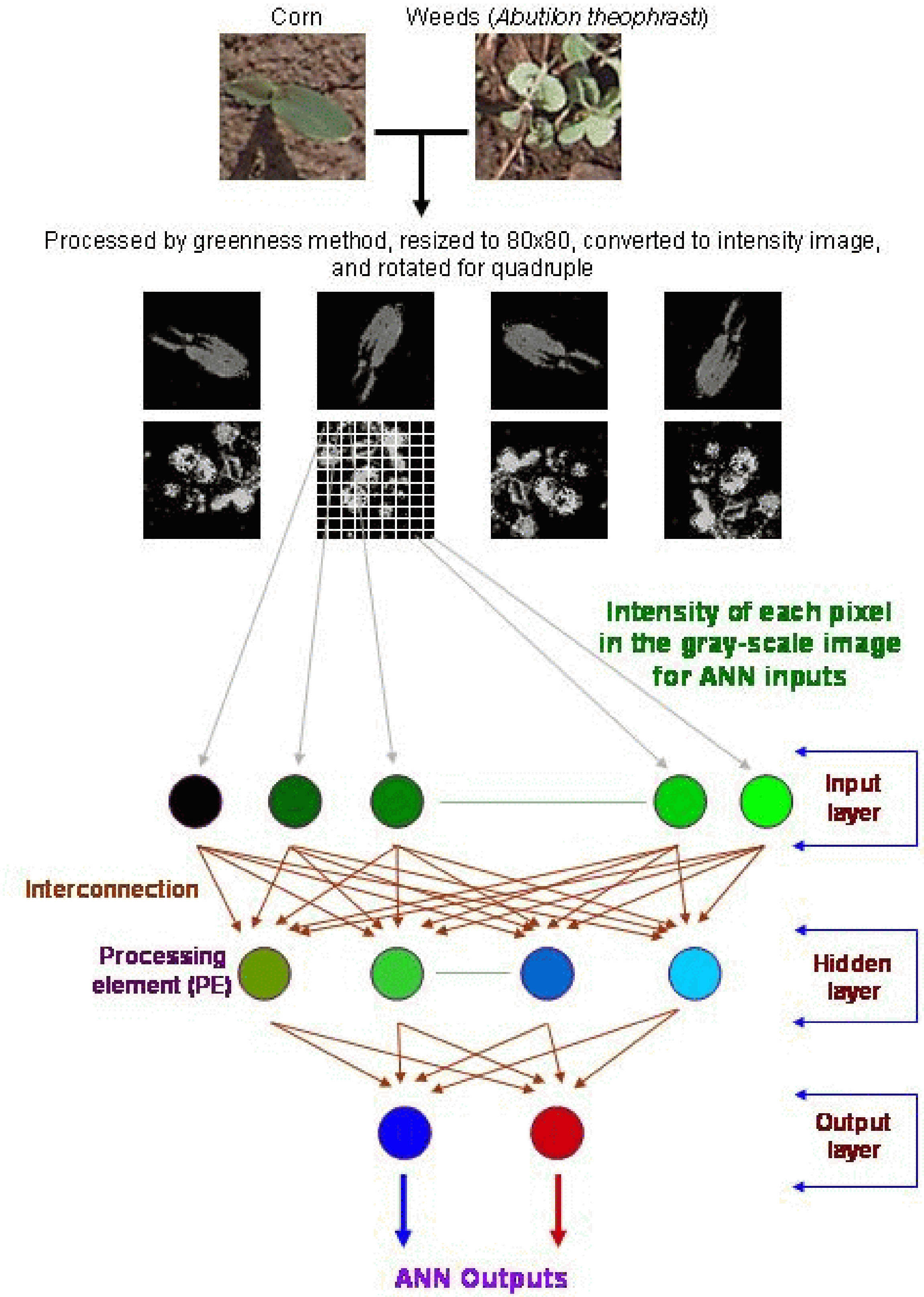

Fig. 1. A general scheme of image recognition for image processing and ANN model development.

Table 1. Success recognition rates (%) of ANN validation for corn and one weed species using greenness method with 80 PEs per hidden layer and intensity for ANN inputs.

File[1]	#1	#2	#3	#2[3]	#1[3]
Corn	100	90	-[4]	-	-
Abutilon theophrasti	40	92	-	-	-
Corn	100	98	-	-	-
Agropyron repens	8	4	-	-	-
Corn	76	100	-	90	90
Chenopodium album	62	0[2]	-	40	54
Corn	74	86	92	-	-
Cyperus esculentus	46	38	42	-	-

[1]: Sequence of training files presented to the ANN model for training
[2]: Training failed
[3]: Sequence of the training files changed to repeat the training
[4]: Training image data set not available for this category

Table 2. Success recognition rates (%) of ANN validation for corn and four weed species using greenness method with 80 PEs per hidden layer and intensity for ANN inputs.

File[1]	#1	#2	#3	#4	#5
Corn	28	50	64	54	58
Abutilon theophrasti	16	20	26	46	56
Agropyron repens	14	2	10	16	22
Chenopodium album	48	38	28	26	20
Cyperus esculentus	40	40	48	68	60

[1]: Sequence of training files presented to the ANN model for training

Table 2 contains the results when an ANN with 80 PEs in the hidden layer was trained to classify images as corn or one of four weed species, specifically. These results are clearly unsatisfactory. The best recognition rate for corn is 58%, and the best recognition rate for a weed is 60% (*Cyperus esculentus*). In other words, the system would recognize almost 50% of corn plants as weeds and almost 50% of weeds as corn plants. The probability of a correct decision for spraying under such circumstances would be less than 40%. This was unacceptable, and an attempt was made to see whether increasing the number of PEs in the hidden layer could improve the performance of an ANN.

Table 3 presents the results of the ten-fold cross validation for the case where the five plant species, i.e., corn plus four weed species, were to be recognized by the ANN model. The average success recognition rates, standard deviations, and 90% confidence intervals are also given in the table. The relatively low success recognition rates for *Agropyron repens* indicate the high difficulty for ANNs to recognize this weed species from

Table 3. Success recognition rates (%) of ANN validation for ten-fold cross validation.

PEs/hidden layer	Fold[1]	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	Ave[4]	SD[5]	90% confidence interval[6]
100	Corn	96	98	84	84	98	90	74	82	68	62	83.6	11.8	[68.5, 98.7]
	Abutilon theophrasti	2	34	30	20	4	6	22	12	16	12	15.8	9.6	[3.5, 28.1]
	Agropyron repens	0	0	0	0	2	2	0	2	0	0	0.6	0.9	[0.0, 1.8]
	Chenopodium album	12	14	28	18	14	30	10	28	12	6	17.2	8.3	[6.6, 27.8]
	Cyperus esculentus	12	24	34	42	18	50	14	32	36	36	29.8	10.8	[16.0, 43.6]
	All weeds[2]	26.0	35.0	58.0	58.5	30.0	43.5	34.5	45.5	39.0	49.0	41.9	9.6	[29.6, 54.2]
	Each weed[3]	6.5	18.0	23.0	20.0	9.5	22.0	11.5	18.5	16.0	13.5	15.9	4.4	[10.2, 21.5]

[1]: Fold sequence for cross validation
[2]: All four weed species treated as different objects but recognized as the same
[3]: All four weed species treated and recognized as different objects
[4]: Average success recognition rate of ten-fold cross validation
[5]: Standard deviation
[6]: 90% confidence interval [mean ± 1.28 SD]

Table 4. Success recognition rates (%) of ANN validation with more RAM to increase the computational ability of ANNs.

PEs/hidden layer	File[1]	#1	#2	#3	#4	#5
100	Corn	28	54	64	54	62
	Abutilon theophrasti	16	16	14	10	12
	Agropyron repens	14	2	2	0	0
	Chenopodium album	48	32	20	14	6
	Cyperus esculentus	40	36	42	52	36
	All weeds[2]	64.5	63.0	62.0	52.0	49.0
	Each weed[3]	29.5	21.5	19.5	19.0	13.5
200	Corn	12	52	54	46	54
	Abutilon theophrasti	8	40	52	70	74
	Agropyron repens	10	8	14	4	12
	Chenopodium album	52	52	26	30	30
	Cyperus esculentus	54	52	32	64	62
	All weeds	69.5	73.0	73.0	77.5	81.0
	Each weed	31.0	38.0	31.0	42.0	44.5
300	Corn	28	48	86	82	88
	Abutilon theophrasti	14	12	14	14	14
	Agropyron repens	8	4	0	0	0
	Chenopodium album	54	40	24	26	8
	Cyperus esculentus	24	36	16	20	16
	All weeds	57.5	62.5	28.5	25.5	21.5
	Each weed	25.0	23.0	13.5	15.0	9.5
400	Corn	26	66	66	18	12
	Abutilon theophrasti	24	20	28	28	46
	Agropyron repens	8	12	4	0	0
	Chenopodium album	54	48	24	10	0
	Cyperus esculentus	56	26	48	80	66
	All weeds	71.5	65.0	65.5	92.5	90.5
	Each weed	35.5	26.5	26.0	29.5	28.0

[1]: Sequence of training files presented to the ANN model for training
[2]: All four weed species treated as different objects but recognized as the same
[3]: All four weed species treated and recognized as different objects

Table 5. Four cases for the investigation of various ANN parameter settings.

	Various settings for ANN architecture
Case 1	100 x100 images used instead of 80 x 80, 10 000 inputs of ANNs
Case 2	Momentum factor set to 0.99 and 0.50 instead of 0.975
Case 3	Even distribution of training data, 200 images for each plant object
Case 4	2 hidden layers, 200 PEs in each layer

corn. This problem may be caused by high similarity of shapes between two plant species when the shapes' green pixels have similar relative positions in the images. The results indicate that most of the ten-fold success recognition rates are within the 90% confidence intervals. This confirms that the ANN models are getting appropriate training and that their results are reliable and not dependent on the particular set of images used for training and testing. The calculation took more than two weeks of continuous computing on a Pentium II 300 MHz computer. It was estimated to take more than four months of continuous computing to perform the ten-fold cross validation for each case in Tables 4 to 6. Because the results from Table 3 indicated that ANN models were getting proper training and testing with our current approach, as confirmed by the ten-cross validation, it was decided that no further ten-fold cross validation would be carried out.

The computational ability of ANNs, associated with the number of PEs in the hidden layer, was influenced by the amount of RAM. The relatively low amount of RAM can limit the computational ability of ANNs. This limitation can cause insufficient training. Thus, the amount of RAM was upgraded to attempt to increase the computational ability of ANNs. Table 4 gives recognition rates for various numbers of PEs in the hidden layer after upgrading the computer from 128MB RAM to 256MB RAM. Although in many cases the success with respect to any or all of the weed species was unacceptable, some ANNs correctly classified images in approximately 80% of the cases presented. For the ANN with 200 PEs in the hidden layer, corn is still correctly classified only for 54% of the images presented, but weeds are also correctly classified as not-corn at a rate of 81%. This is perhaps the most encouraging case to prove ANN's ability for image recognition, because it is far more important to recognize a non-crop plant as such, given that it is possible to exclude row crop plants altogether from image collection, even in a real-time system. However, due to the limit to which the computer's available physical memory could be upgraded and to the insufficiency of the ANN software's memory management, the number of PEs in the hidden layer could not be increased further. The largest hidden layer, composed of 400 PEs, was still small in comparison to the input layer, which contained 6400 PEs. It is difficult to draw a definitive conclusion as to whether the upgraded RAM could help improve the ANN performance. During the image processing, it was found that even when the ANN model was built with 400 PEs in the hidden layer, the largest ANN architecture which required the longest processing time, the model required only 60 seconds or less for 250 images, or 0.24 seconds per image. This implies that a properly trained ANN model is ideally suited for real-time herbicide applications in precision agriculture which requires very fast execution times.

Table 5 shows four cases with various ANN architectural settings attempting to improve the ANN model performance. The ANN with 200 PEs in the hidden layer was used in this part of the study because, as shown in Table 4, the weed recognition rate is better than the recognition rate for ANNs with different numbers of PEs in the hidden layer. Table 6 contains the results of our attempts to improve the ANN model performance in these four cases. In Case 1, 100x100 pixel images were used (i.e. prior to reducing to 80x80 by nearest neighbour

Table 6. Success recognition rates (%) of ANN validation by ANNs with various parameter settings.

	File[2]	#1	#2	#3	#4	#5
Case 1[1]	Corn	10	66	74	68	34
	Abutilon theophrasti	22	20	22	16	6
	Agropyron repens	14	0	0	0	0
	Chenopodium album	44	38	14	36	18
	Cyperus esculentus	64	46	44	54	82
	All weeds[3]	80.5	61.5	61.5	66.5	87.0
	Each weeds[4]	36.0	26.0	20.0	26.5	26.5
Case 2	Corn	12	52	54	46	54
	Abutilon theophrasti	8	40	52	70	74
	Agropyron repens	10	8	14	4	12
	Chenopodium album	52	52	26	30	30
	Cyperus esculentus	54	52	32	64	62
	All weeds	69.5	73.0	73.0	77.5	81.0
	Each weed	31.0	38.0	31.0	42.0	44.5
Case 3	Corn	7	31	36	-[5]	-
	Abutilon theophrasti	27	20	23	-	-
	Agropyron repens	26	26	28	-	-
	Chenopodium album	53	41	48	-	-
	Cyperus esculentus	45	44	50	-	-
	All weeds	90.0	87.0	85.0	-	-
	Each weed	38.0	33.0	37.0	-	-
Case 4	Corn	26	52	70	70	74
	Abutilon theophrasti	16	28	30	22	18
	Agropyron repens	14	14	6	0	0
	Chenopodium album	44	18	16	24	4
	Cyperus esculentus	58	36	48	42	18
	All weeds	71.0	71.5	57.5	50.0	32.0
	Each weed	33.0	24.0	25.0	22.0	10.0

[1]: Various parameter settings for ANNs for each case listed in Table 5
[2]: Sequence of training files presented to the ANN model for training
[3]: All four weed species treated as different objects but recognized as the same
[4]: All four weed species treated and recognized as different objects
[5]: Training image data set not available for this category

interpolation). This case does not exhibit a significant improvement over the corresponding results in Table 4. In Case 2, different momentum factors did not cause any noticeable impact on the ANN performance because the results are almost the same as those in Table 4. The results of Case 3 (even distribution of training data and 200 testing images for each plant species) and Case 4 (first hidden layer with 200 PEs, and addition of a second hidden layer also with 200 PEs) indicate that both methods did not help to improve the recognition rates.

The difficulties experienced by ANN models in this study could be caused by thecomputer's insufficient processing ability and the ANN software's inadequate memory management system. To reduce the need for computational power and memory, the ANNs had only 80 to 400 PEs in the hidden layer to process the information from 6400 inputs (80x80 pixels) and 1736 training images. To accommodate the limitations imposed by the computer's hardware, the size of images was reduced to 80x80 pixels, which eliminated some information from the original images. The ANNs should be further tested with a larger hidden layer and images with higher resolution when the processing power and the memory of the computer can be upgraded. The other challenge posed to the ANNs could be that the weed images contained varied numbers of weeds of the same species, thereby impeding the ANNs ability to distinguish weeds. The complexity of weed images may also be overcome by using more training images with the models. Although limited success was achieved with the back-propagation ANN in differentiating corn from weeds in this study, ANN-based recognition models should be investigated further by using other ANN models, such as Learning Vector Quantization (LVQ), because they are ideally suited for real-time applications which require very fast execution times.

CONCLUSIONS

Using back-propagation ANNs to distinguish 80x80 images, the highest success recognition rate was 100% for corn, 92% for *Abutilon theophrasti*, about 62% for *Chenopodium album*, and 80% for *Cyperus esculentus*. The ANN model required less than one minute to process 250 images. However, the evaluation of ANNs could not be fully exploited in this study due to hardware limitations and insufficient memory management by the ANN software. This study seems to indicate that it is highly unlikely that back-propagation ANNs with structures that can be handled by commercially-available computers can be trained to assimilate visual information to an extent permitting high success rates in the weed classification problem relevant to precision spraying, unless the recognition problem is simplified. It is perhaps unnecessary to include the crop plant in the training, and the question of distinguishing between the crop and a weed, be it specific or general, is irrelevant in a row-cropping situation. This leads to the conclusion that a far simpler approach might be to implement machine vision and image processing in such a way as to exclude the crop row. In this situation, it is clearly a simple matter to determine greenness area. One must then be willing to accept that the economic threshold be defined on the basis of inter-row green coverage, whether or not the ultimate precision is achieved.

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