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BARD

FINAL REPORT

PROJECT NO. US-2415-94

Expert Sensor for Site-Specific Application of Agricultural Chemicals

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1999

497033

Expert Sensor For Site Specific Application of Agricultural Chemicals

BARD Project No. US-2415-94R
Final Scientific Report

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Date: 1 September 1998

BARD Project Number: US-2415-94R

Project Title:

Expert Sensor for Site-Specific Application of Agricultural Chemicals

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Project Start Date: 8 August 1995

Type of Report: 1st Annual 2nd Annual Final X

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Sponsored Programs

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1946 - 1998

*The people walking in darkness have seen a great light;
On those living in the land of darkness a light has dawned.*
Isaiah 9:2

Expert Sensor for Site-Specific Application of Agricultural Chemicals

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Expert Sensor for Site-Specific Application of Agricultural Chemicals

Abstract

In this work multispectral reflectance images are used in conjunction with a neural network classifier for the purpose of detecting and classifying weeds under real field conditions. Multispectral reflectance images which contained different combinations of weeds and crops were taken under actual field conditions. This multispectral reflectance information was used to develop algorithms that could segment the plants from the background as well as classify them into weeds or crops. In order to segment the plants from the background the multispectral reflectance of plants and background were studied and a relationship was derived. It was found that using a ratio of two wavelength reflectance images (750nm and 670nm) it was possible to segment the plants from the background. Once this was accomplished it was then possible to classify the segmented images into weed or crop by use of the neural network. The neural network developed for this work is a modification of the standard learning vector quantization algorithm. This neural network was modified by replacing the time-varying adaptation gain with a constant adaptation gain and a binary reinforcement function. This improved accuracy and training time as well as introducing several new properties such as hill climbing and momentum addition. The network was trained and tested with different wavelength combinations in order to find the best results. Finally, the results of the classifier were evaluated using a pixel based method and a block based method. In the pixel based method every single pixel is evaluated to test whether it was classified correctly or not and the best weed classification results were 81% and its associated crop classification accuracy is 57%. In the block based classification method, the image was divided into blocks and each block was evaluated to determine whether they contained weeds or not. Different block sizes and thresholds were tested. The best results for this method were 97% for a block size of 8 inches and a pixel threshold of 60.

A simulation model was developed to: 1) quantify the effectiveness of a site-specific sprayer 2) evaluate influence of different design parameters on efficiency of the site-specific sprayer. In each iteration of this model, infected areas (weed patches) in the field were randomly generated and the amount of required herbicides for spraying these areas were calculated. The effectiveness of the sprayer was estimated for different stain sizes, nozzle types (conic and flat), nozzle sizes and stain detection levels of the identification system. Simulation results indicated that the flat nozzle is much more effective as compared to the conic nozzle and its relative efficiency is greater for small nozzle sizes. By using a site-specific sprayer, the average ratio between the spraying areas and the stain areas is about 1.1 to 1.8 which can save up to 92% of herbicides, especially when the proportion of the stain areas is small.

Expert Sensor for Site-Specific Application of Agricultural Chemicals

Research Objectives

The general objective of this project was to develop sensor technologies which permit chemicals to be applied site-specifically on plants in a manner which minimizes the quantity required to control crop pests. The specific objectives were:

1. Develop machine vision hardware and image processing software to locate small seedlings, distinguish weeds from the cultivated crop, and measure parameters which affect the quantity and location of chemical to be applied;
2. Develop image processing and pattern recognition algorithms which can interpret the sensed data in real-time, and;
3. Develop artificial intelligence algorithms (expert systems, neural networks, *etc.*) capable of making real-time decisions concerning when and how much chemical to apply, based on perceived conditions.

Methodology

Objective 1: Machine Vision Sensor Technologies

Multi-spectral images of cotton, corn, and soybeans and their common weeds were collected by an acousto optical tunable filter¹ and digitized by a personal computer (Figure 1). In Israel, a CCD Camera (Pulnix Model TM 657) with a resolution of 510 x 256 pixels and a frame grabber (Bargold IVP 150) were used to collect images in cotton fields. The equipment used at Purdue University consisted of a Brimrose Model TVA 100 AOTF, a Dolch P-133 portable computer running Windows 95™, an Imaging Technologies IC-PCI framegrabber, and a Pulnix TM-80 CCD camera. Figure 2 illustrates the complexity of a typical field scene, and the resulting multi-spectral reflectance curve.

In order to acquire the multi-spectral data, computer programs were written to control and synchronize camera exposure, the AOTF's Direct Digital Synthesizer (DDS) which produced the Radio Frequency (RF) signal for tuning the filter to the desired band-pass wavelength. Leaf

¹ Brimrose Model TVA100-.5-1.0 Mention of commercial products is for informational purposes only and does not imply endorsement by the investigators nor their respective institutions to the exclusion of other products.

reflectance changes with wavelengths and differences in camera sensitivity to low light conditions gave rise to two approaches in field data collection.

At Purdue, a fixed exposure interval was used. Images were captured, stored on a PCMCIA disk and transferred daily to the Agricultural and Biological Engineering Department Server. In the summer of 1996 images were taken every 10 nanometers (nm) from 500 to 1000 nm. At some wavelengths, the amount of radiation passed by the AOTF was very small, and the resulting images were very dark. In 1997 images were taken at 5 nm increments, with the majority of images taken from 650 to 850 nm. A practical detection system must be robust enough to compensate for changes in illumination, shadows, and other noise such as the slight motion of plants from image to image during the time required for the AOTF to settle on the new wavelength. Thus, the images taken at Purdue are typical of field conditions and provide realistic challenges for the image processing and pattern recognition software. Approximately 200 sets of these images (10,000 total) may be found at:

http://danpatch.ecn.purdue.edu/~agvision/Tiff_images/Contents.html

Access may be obtained by contacting gem@purdue.edu.

Figure 1. Schematic diagram of Acusto-Optical-Tunable-Filter (AOTF) and computer

The second approach, pursued in Israel used absolute reflectance values, which required the calibration of dynamic range of the imaging-system for each wavelength. The calibration parameters that control it are (1) the exposure time (2) the illumination intensity, spectral characteristics and direction and (3) the object reflectance characteristics. The use of constant exposure time limits the dynamic range, resulting in under or over exposed images. The optimum exposure time depends on the spectral responsivity of the AOTF and the CCD chip. This is because the AOTF efficiency as well as the CCD responsivity varies considerably over the covered spectral range. The AOTF efficiency peaks at around 700 nm and declines drastically below 525 nm and above 950 nm. The CCD responsivity also peaks at about 700 nm (with IR filter removed), remaining at an acceptable level down to 500 nm, but drops rapidly above 900 nm. Therefore, a combination of filter's efficiency and CCD responsivity was used to determine optimal exposure time for each wavelength.

In Israel, cotton plants were grown in a field adjacent to the Institute of Agricultural Engineering at Volcani Center. Images were taken when seedlings were in the stage of 2 to 4 leaves. The imaging system was mounted on a moveable platform that was carried by a tractor to the field. The tractor traveled over the crop rows and stopped at designated locations for image acquisition. While standing above the crop row, multispectral images were acquired at the range of 500-1000 nm with steps of 5nm. Images were saved to the disk for later analysis. At each location, 100 images were acquired. The images were also recorded on CD-ROMs for archiving and off-line analysis. The scene was illuminated with direct sunlight with no special illumination arrangements. The images were taken between 11:00-15:00 hours each day, so that the sun was close to its zenith at the time of sampling. When clouds partially obscured the sun, image acquisition was terminated.

Figure 2. Typical grayscale image at 750 nm on the left and the reflectance spectrum of the plants and soil on the right, as measured by the AOTF and CCD camera.

Objective 2: Image Processing and Pattern Recognition Algorithms

Robust statistics algorithms are based on histograms describing the frequency of appearance of individual multi-dimensional signal samples (Yaroslavsky and Eden, 1996). A simple algorithm is available for computing the distribution histograms. Mathematically, the algorithm is described as a convolution:

$$h(\bar{m}) = \frac{1}{N_1 N_2} \sum_{k=0}^{N_1-1} \sum_{l=0}^{N_2-1} \delta(\bar{m} - \bar{m}_{k,l}) \dots\dots\dots [1]$$

where $\bar{m}_{k,l}$ is the vector of values of the component at sample (k, l) of the signal, and $\bar{m}$ is the vector of the histogram argument component values.

A histogram may characterize an entire observed image, or individual image fragments. In the last case, it is called *local histogram*. When local histograms of overlapping image fragments are needed, a recursive mathematical expression, based on expression [1] may be formulated.

Mean values of gray levels and their variance measured over local histograms, provide a good estimate for textural properties of images. However, if an image consists of some randomly distributed details on a background, mean and variance are unsatisfactory, since statistical characteristics of the details and the background in such estimates are mixed. This mixing may be overcome with the help of *robust estimates* of distribution parameters. The term *robustness* implies immunity to small deviation from the prior assumption.

Referring to the distribution parameter estimates, robustness implies insensitivity to small “admixture” to distribution. In a sense, one may regard the robust estimates to be adaptive to basic distribution. Best known and best studied are the following robust estimates of the mean: the distribution median and the alpha-trimmed mean.

The *distribution median* is a value, MED, of a sample element, such that the same number of sample elements has value below and above MED. The median may be found by placing the elements of the sample in a series, in increasing order of magnitude, in *variational row* $V(r)$, $r=0, 1, \dots, N-1$.

The *alpha-trimmed mean* (ATM) is the arithmetic mean of the elements of the variational row that are minimum α elements apart of its ends,

$$ATM = \frac{1}{N - 2\alpha} \sum_{k=\alpha}^{N-1-\alpha} V(r) \dots\dots\dots [2]$$

These estimates appear to be robust to the distribution admixtures affecting its tails. Thus, applied to images with small details on much larger background, these provide a good estimate of the mean value of the background.

The above robust statistics algorithms were applied for weeds detection on the acquired data. Due to the high-dimensionality of the signal, only 660 nm and 800 nm image channels were used. First, A 2D histogram of 600 nm and 800 nm image channels was built. Then, the histogram was used to segment the plants, weeds and cotton from the soil background. Second, we computed the quasi-spread parameter in a 3×3 sliding window. Quasi-spread parameter gives a robust variance estimate, providing an edge map of the scene. Third, we counted the number of threshold crossing times in sliding windows 1×50 and 50×1 and obtained two resultant images. Fourth, for each pixel, a decision was made – cotton or weed – based on the number of threshold crosses at the examined pixel.

MLVQ learning algorithm: At Purdue, a neural network was developed to detect weeds among crops based upon a modified learning vector quantization (MLVQ). The modified learning vector quantization network is a hybrid network that uses both supervised and unsupervised learning (Haralson:1998b) to train its neurons. This network is a variation of the learning vector quantization (LVQ) first proposed by Kohonen, 1986, and described in Haykin,1994. The MLVQ

was obtained by replacing by replacing the self-organizing feature map (SOFM) of the LVQ with a modified self-organizing feature map (MSOFM). The MSOFM was developed by replacing the time-varying learning rate of the self-organizing feature map with a constant learning rate and a binary reinforcement function (Haralson, 1998b). The MLVQ is a two-layer network whose first layer consists of the MSOFM network while the second one is a linear layer that maps the neurons from the MSOFM network to a specific class. Therefore the neurons in the MSOFM layer form subclasses that are associated with a specific class in the second layer. The ability to combine subclasses into classes allows the MLVQ network to form complex boundaries that would be otherwise impossible with only a competitive network, which in turn increases the classification accuracy of the network (Haykin, 1994).

Let $\{w_j \mid j = 1, 2, \dots, N\}$ denote the set of weight vectors that correspond to the feature map and $\{x_i \mid i = 1, 2, \dots, L\}$ denote all of the input vectors to be used in training and for which $L \gg N$. x_i is selected at random from the above set of input vectors and w_c is defined to be the weight vector of the feature map which is closest to the input vector x_i .

$$\begin{aligned} w_c(n+1) &= w_c(n) + \kappa + \psi & \text{for } C_{w_c} = C_{x_i} \\ w_c(n+1) &= w_c(n) - \kappa - \psi & \text{for } C_{w_c} \neq C_{x_i} \\ w_j(n+1) &= w_j(n) & \text{otherwise} \end{aligned}$$

$$\begin{aligned} \kappa &= \alpha[x_i - w_c(n)] \\ \psi &= \eta \rho(n) \text{sgn}_v[x_i - w_c(n)] \end{aligned}$$

$w_c(n+1)$ is the weight vector after updating; $w_c(n)$ is the weight vector before updating; κ is the adaptation term that corresponds to the difference between the input vector and the weight vector multiplied by the constant gain α ; ψ is the binary reinforcement term; C_{x_i} is the class of the input vector x_i , while C_{w_c} is the class of the weight vector $w_c(n)$. $w_j(n)$ is the rest of the weight vectors that are farther away from x_i than w_c ; η is the gain of the binary reinforcement term while $\text{sgn}_v[x_i]$ is the signum function defined by the following:

$$\text{sgn}_v[x_i] = (\text{sgn}[x_{i1}(n)], \text{sgn}[x_{i2}(n)], \dots, \text{sgn}[x_{iN}(n)])^T$$

where $\text{sgn}[\tau]$ is the signum function such that $\text{sgn}[\tau]=0$ if $\tau=0$, $\text{sgn}[\tau]=1$ if $\tau>0$, and $\text{sgn}[\tau]=-1$ if $\tau<0$. Finally, the random variable $\rho(n)$ can be defined as follows:

$$\rho(n) = R \cdot u[\text{rand}(N_{\max} - n) - \text{rand}(N_{\max})]$$

where R is a binary random variable with probability $P(R=1)=0.5$; $\text{rand}(y)$ is a function that generates random numbers between 0 and y ; $N_{\max}$ is the maximum number of iterations while n is the current iteration; $u(m)$ is the step function defined by $u(m)=1$ for $m \geq 0$ and $u(m)=0$ for $m < 0$.

As described in Haralson, 1998b, it is necessary to use the constant adaptation gain and the binary reinforcement function to replace the time-varying learning rate in the proposed MLVQ, since using only one of them will have an adverse effect on the learning algorithm in general. For example, if only a constant adaptation gain is used, the weight vector $w_j(n)$ will never be able to converge to its optimal value w_j^* and in fact will always reside around a region K_δ , which is determined by the second Euclidean norm of the expected deviation vector $\bar{v}_j(n)$. $\bar{v}_j(n)$ represents the average difference between the weight vector $w_j(n)$ and the optimal weight vector w_j^* . On the other hand, if only the binary reinforcement function is used as a replacement, it is possible for $w_j(n)$ to converge to the optimal weight vector w_j^* , however it requires a long convergence time. Using the constant adaptation gain and the binary reinforcement function to replace the time-varying learning rate avoids the disadvantages each has on its own, while retaining the merits which enhance learning. It should also be noted that the gain of the first regressive term κ , should generally be greater than the gain of the second regressive term ψ (Goodwin, 1984), although not much greater. Making the gain of the binary reinforcement term larger than that of the constant adaptation gain causes the initial states of the weight vectors to be found far from the optimal weight vectors. This will require the network a large convergence time to achieve the optimal solution, if convergence is possible at all. If on the other hand, the gain of the binary reinforcement is made very small in comparison to the constant adaptation gain, its effect will be ignored and the network will not be able to converge to the optimal solution.

MLVQ training algorithm: A training algorithm was developed using ideas found in the function *trainlvq.m*, which is part of the Matlab Neural Network Toolbox, and using the MLVQ rules described previously. The first step is picking an input vector at random from the set of all

training vectors presented to the network. Using the distance measure found in the following equation, the distances between all the weight vectors and the chosen input vector are found.

$$dist_j(n) = \sqrt{\sum_{k=1}^N (x_{ik} - w_{jk}(n))^2}$$

x_{ik} is the k -th element of the input vector x_i , $w_{jk}(n)$ is the k -th element of the j -th weight vector $w_j(n)$, N is the dimension of the input vectors and weight vectors and n is the current iteration. Using the previously calculated distances, the weight vector that is closest to the input vector can then be found using the following equation:

$$c = \arg_j \max[-dist_j(n)] \quad j = 1, 2, \dots, M$$

c is the index of the winning weight vector $w_j(n)$, and M is the total number of weight vectors in the feature map layer.

The weight vector that is found to be the closest to the input vector x_i is said to *win* the competition and can be updated according to the learning rules described previously. However, since this winning weight vector (or neuron) may or may not be in the same class as the input vector, it is also desired to find the closest neuron in the same class as that of the input vector.

Using the previously calculated distance measures, a new distance measure D_j is calculated in the following equation with which the second competition is performed. The purpose for calculating this new distance measure is to guarantee that the winning neuron obtained from the second competition will always be in the same class as that of the input vector x_i . To accomplish this, a very large constant offset Δ is added to all the distance measures $dist_j(n)$ whose corresponding neurons belong to the same class as the input vector. Another thing this new distance measure accomplishes is to include a bias term β_j that acts as a *conscience* for the neurons. This conscience keeps track of which neurons have won recently and decreases their possibility of winning the next time.

$$D_j = \begin{cases} -dist_j(n) + \Delta + \beta_j & \text{if } C_{w_j} = C_{x_i} \\ -dist_j(n) + \beta_j & \text{else} \end{cases}$$

Once the new distance measures are calculated, a second competition is performed with the following equation.

$$c_2 = \arg_j \max[D_j] \quad j = 1, 2, \dots, M$$

where M is the total number of weight vectors in the feature map layer and c_2 is the index of the winning weight vector.

Following the second competition the two winning neurons are compared with each other. If these neurons are found to be the same one, then only the weight vector for that neuron has to be updated according to the learning rules. On the other hand, if the neurons are found to be different, both weight vectors get updated according to the learning rules. Finally, the bias terms associated with each neuron are updated to reflect which neurons have won recently, after which the whole procedure is repeated again until the maximum number of iterations or the desired mean square error is reached.

Now that the mechanism for the second competition has been defined, it is necessary to explain how the bias term β_j is obtained and how it is updated after every iteration. The bias term β_j is defined as follows:

$$\beta_j = e^{1-\ln(\zeta_j)} \quad \text{for } j = 1, 2, \dots, M$$

The value ζ_j is initialized according to equation below where S is the number of classes into which the data is to be classified.

$$\zeta_j = \frac{1}{S} \quad \text{for } j = 1, 2, \dots, M$$

Once it has been initialized, ζ_j will be updated after every iteration with the following equation:

$$\zeta_j = \begin{cases} \zeta_j & \text{if } C_{w_j} \neq C_{x_i} \text{ and } j \neq c_2 \\ \zeta_j \cdot \mu & \text{if } C_{w_j} = C_{x_i} \text{ and } j \neq c_2 \\ (\zeta_j \cdot \mu) + \nu & \text{if } C_{w_j} = C_{x_i} \text{ and } j = c_2 \end{cases}$$

where μ is a bias time constant set by the user and ν is defined as $1 - \mu$, j is the index of the neuron to be updated and c_2 is the index of the neuron that won the second competition as defined previously.

The purpose of the bias, as mentioned previously, is to act as a conscience for the neurons. It reduces the possibility of one neuron continuously winning by decreasing the value of the bias term β_j that is added to the winning neuron. It can also be noticed that only those biases that correspond to the neurons in the correct class are modified. The reason for this is that if a neuron belonging to one class keeps winning because it is close to the input vectors of the opposite class, it is desirable for it to keep winning so that it will be pushed away from this class towards the class it truly belongs to. On the other hand, for the neurons that belong to the same class as the input vector, it is desired to spread the weights as effectively as possible throughout the input space for that class in order to reduce the mean square error of the classification.

Objective 3: Algorithms for Chemical Application Decisions

A model was developed to simulate site-specific spraying and to quantify the potential savings in chemicals compared to traditional, uniform applications. The following assumptions were made:

1. The shape of weed patches are circular: usually before seeding the field is treated to avoid weeds, and in these fields the weed patches start in a small center and expand in a circle.
2. Complete covering of the patch/stain is required: when weeds are detected they must be totally covered by spray.
3. The infected area is sprayed by a rectangular sprays, the width of the rectangular depends on the width of the nozzle spray cut and the length of the rectangular is the distance between the starting point and the ending point (Figure 3).
4. The response time of the sprayer is negligible. The assumption is that the effect of the delay time can be overcome by the control system by synchronization with the optical system.
5. A worst case analysis is performed. The analysis ignores the possibility of overlap between stains, and assumes large distance between stains, so every stain should be sprayed separately. In cases with overlapping stains or when distance between stains are small, the spraying will operate continuously (same as for large stains).
6. The efficiency of the system was checked in optimal conditions to obtain an upper limit for efficiency evaluation. The only error considered was detection. Additional sources of errors such as vehicle and wind velocities, effect of system delays, errors due to mechanical system were not taken into account in the analysis.

Figure 3: The actual sprayed area with: flat nozzle (a), conic nozzle (b).

Simulation parameters: Stains of different sizes were generated randomly according to the following sizes:

Small	=	0.3 - 1 m
Medium	=	1 - 2 m
Large	=	4 - 6

Two types of nozzles were evaluated: A conic nozzle with a solid cone-shaped spray pattern with a round impact area and a flat nozzle which has a flat spray pattern (Figure 4).

Figure 4: Spray impact area for: a. conic nozzle, b. flat nozzle.

Different sizes of nozzle sprayed band-width (spray coverage) were estimated from 10 cm to 120 cm. The width of the band depends on the nozzle type and size, spray angle and spray height (Figure 5). The operating pressure and the liquid viscous effect on spray angle. The simulation model estimated the band-width, from the band-width the nozzle parameters can be calculated.

Figure 5: Sprayed coverage according to sprayer parameters.

Three different probabilities detection level of the identifying system were considered: 50%, 70% and 95%.

Model implementation: The simulation model was implemented in Matlab. A thousand iterations of this model for each test case (stains size, band-width and nozzle type) were generated. The simulation included the following steps:

1. Generate a weed location and weeds size according to the required range (small, medium or large)
2. Compute the identification probability of the stain and calculate the rate of undetected stains.
3. Calculate the required spraying area to get a complete covering of the infected area. Using a conic nozzle required to start spraying before the stain and ended after (Figure 3b.) due to the circular shape of the conic spray pattern and the constraint for a complete covering.
4. Calculate the proportion between the cumulative stains area and the required spraying area. This proportion is important for estimating the amount of required herbicide materials and the efficiency of the design (herbicides waste and pollution)

Simulation measures: The simulation measured the amount of sprayed area which was required to obtain a complete covering of the weeds patch depending on the sprayer parameters (nozzle type, nozzle size and detection level) and the stain size. The model calculated the proportion between the cumulative stains area and the required sprayed area. For example, if the proportion is 1.2 this implies that the sprayed area will be 1.2 times of the stain area and there is 20% waste of material. This proportion estimates the amount of required herbicide materials and indicates the inefficiency of the specific design (herbicides waste and pollution). The greater the IFF the lower the efficiency and the optimal proportion is 1.

$$\text{Inefficient Index} = \frac{\text{Spraying Area}}{\text{Infected Area}}$$

Sensitivity analysis: Sensitivity analysis was performed for the following parameters: stains size, shape and size of the nozzle and number of nozzles. It is clear that the efficiency of the performance is greater as the number of nozzles are increased and the smaller the sprayed bandwidth the more efficient is the spraying. However, this results in higher cost of the spraying system.

Results and Discussion

Machine Vision and Image Processing Software

Optimum exposure time at each wavelength was determined by recording the spectral response of a white reference surface for various exposure intervals. The reflectance of the white reference surface, as recorded by the camera, was plotted against exposure time and wavelength, as shown in Figure 6. Exposure time started at normal CCIR exposure, 25 ms, and increased to 1000 ms, with steps of 25 ms. Exposure of more than 1 s was not considered, because the image noise due to thermal noise of the CCD detector became significantly high. The following conclusions can be drawn from the response in Figure 6:

- (1) Exposure of one second causes the CCD detector to reach saturation in the wavelength range of 600 nm to 820 nm. In this range, the optimum exposure time can be determined from the longest exposure time at which the CCD detector is still not saturated.
- (2) At wavelengths from 500 nm to 600 nm and from 820 nm to 1000 nm, the CCD does not reach saturation, even at the maximum exposure time. Therefore, exposure time for these ranges was set to one second.

Figure 6. Relative response of the AOTF and CCD image sensor

In order to maintain maximum possible dynamic range throughout the whole spectral range, a contour line with constant response was plotted, as shown in Figure 7. From this graph, the exposure time for each wavelength can be found. Using this graph, the camera's exposure was controlled for optimum exposure.

Figure 7. Contour of constant response as a function of wavelength and exposure time

The illumination intensity and spectral characteristics were assumed to be constant. No special illumination arrangements were made; the scene was illuminated by direct sunlight.

Detection and distinction between cotton and weeds using direct information from reflectance data are not so obvious. There is a large overlap in the spectral response of cotton plants and weeds. Additionally, orientation and geometrical relation is not constant and predetermined. If the detection is to be based on spectral data only, more sophisticated analysis has to be adopted. Nevertheless, since the developed system is not just a spectroscopic system, but has inherent imaging capabilities, the geometric and structural differences of cotton plants and weeds can be exploited in order to accomplish the detection.

It is easy to distinguish between soil and cotton by combining reflectance information at 660 nm and 800 nm. At 660 nm, which belongs to the red part of the visible spectrum, leaves appear as dark since they absorb most of the light energy, while soil appears as light colored. At 800 nm, leaves are very light colored while soil is much darker. Combination of the information provided in those two spectral channels enables accurate and robust distinction between leaves and soil.

The analysis was made on a data set of 104 images, where 45 images were cotton only, 43 images were weed only, and 16 combined cotton and weed in the same image. The images were segmented manually, and the area covered by cotton and weeds was measured. The weed detection algorithm was then applied on the data set. The performance of the algorithm was evaluated by comparison of the area detected as weeds by the automatic algorithm, AW, to the area that was manually labeled as weeds, MW. The ratio of the two areas, gives an estimate of the overall accuracy that the algorithm can detect areas with weeds. In addition to that, the error of the algorithm was evaluated by summing up the area that was identified by the algorithm as weeds, when no weeds were present in the image. Figures 8, 9 and 10 summarize the results of weed detection algorithm developed at Volcani.

Figure 8. Automatic versus manual detection

Figure 9. False weed detection alarms

Weed and Cotton - MW/AW Vs. Series

Figure 10. Automatic versus manual detection results for scenes with weeds and cotton

Figure 8 shows that all weed appearances were found. Moreover, in 60 % of the images the area of the weeds was detected with an accuracy more than 70%. In most of the images the area of the weeds was underestimated. In images that did not contain weeds, the detection algorithm performed with a maximum error of 15%, as depicted in Figure 6. The low error rate in false weed detection implies that a future system based on the present algorithm would have a low incidence of spraying spots that do not contain weeds.

Figure 10 shows the ratio between the actual weed area and the detected weed area for the images that the two plants are overlapped. In most of the images (75%) the detected weed area is more than 80% of the actual weed area that was measured manually. This group of images represent the most difficult case, where there is no physical separation between the weeds and the crop.

Image Segmentation: Examples of using the segmentation algorithm can be seen in Figure 11. The image on the left is the grayscale image for 750 nm while the results of using the segmentation algorithm on the image is on the right. Comparing the original grayscale image to its corresponding segmented image, it is possible to observe that most of the pixels that correspond to plants in the image have been kept, while the rest of the pixels have been set to zero since they correspond to background material. It is also possible to observe that the segmentation algorithm is not 100 % successful at separating every single plant pixel from the background. The two areas where it has trouble segmenting the plant pixels are at the edges of the plants and where the plant falls under a shadow. All the images were taken at a height of 65 inches and the focus adjusted to

yield the best picture. The field of view contained in the image is 21 by 23 inches. The black band running from top to bottom on the left side of the image is caused by the combination of the AOTF and the camera since the field of view of the AOTF was slightly smaller than the camera. Also, in some images a shadow unavoidably caused by the leg of the camera tripod runs across the whole image. Because one of the performance criteria was for the software to be robust and capable of overcoming such noise, temptations to beautify the images were mostly resisted.

Figure 11. Example of the results of applying the segmentation algorithm to a soybean image.

Neural Network: The network was trained for 2000 epochs using three different setups (See Table 1). The rest of the values such as the constant adaptation gain α , the binary reinforcement gain η , and the bias time constant μ were set to the following values for every training:

$$\alpha = \frac{1}{32}$$
$$\eta = \frac{1}{64}$$
$$\mu = 0.99$$

Blocks of 3x3 pixels that contained weeds or crops were taken from each image for the purpose of training. The total number of blocks taken from each image varied between 80 and 340 blocks depending on how many plants were available in the image. A total of 16 series of multi-

spectral images were used to perform the training. Since the images are segmented before they are classified it was only necessary to define two classes for classification purposes, weed or not weed. After the training was performed the neural network was tested using the same setup parameters and wavelength combinations as were used in training. These results were then evaluated to determine the accuracy of the classification results.

Table 1 Parameters which were varied on the neural network during training and testing

Test	Number of Neurons	Number of Wavelengths	Total Combinations
1	20	3	210
2	10	3	210
3	10	2	441

Pixel based error evaluation

The first method that was used to evaluate the results of the MLVQ network was a pixel based evaluation method in which every single pixel value generated by the classifier is compared with a user generated truth map to test for correctness. To be able to do this it was necessary to build truth maps for every image tested. Figure 12 contains the first image to be evaluated and its associated truth map. The grayscale image shown was taken at 750nm under direct sunlight. The truth map was generated by hand using a program designed for this purpose. Figures 13, 14, and 15 contain the test 1 classification results for the image in Figure 12. These results were obtained by testing the network setups mentioned previously with different wavelength combinations. These figures show the percentage accuracy of weed and crop classification with respect to the wavelength combination used. To facilitate the display of this information all the wavelength combinations were numbered sequentially and this number was used to plot the histograms. The results for all 3 tests and 16 images are described by Haralson, 1998.

Figure 12. Original grayscale image (750 nm) and pixel truth map used for evaluation of the neural network (gray=crop, white=weed).

This method was tested only with the first four image scenarios since the map generation for this pixel based approach was a laborious process and required great precision. These maps were used to evaluate the results for all tested combinations. In Figures 13, 14 and 15 the classification accuracy depends on the wavelength combination chosen. The best classification accuracy for weed detection does not occur at the same wavelength combinations as the best classification accuracy for crop detection. For test 1 the best weed classification accuracy obtained is 81.15% at the wavelength combination of 600nm, 790nm, 800nm, whereas the crop classification accuracy for that wavelength combination is only 57.74% which is clearly not the best classification accuracy for crops. There appears to be no significant improvement in using three wavelengths instead of two. The best weed classification accuracy obtained in test 1 where combinations of three wavelengths were used was 81.15% while the best classification accuracy obtained in test 3 where combinations of two wavelengths were used was 80.63%. In the same way the crop classification accuracy for test 1 was 57.74% while for test 3 it was 62.46%. It can be seen from this that there appears to be no significant improvement in classification by adding the extra wavelength.

Figure 13. Test 1 percentage of correctly classified weed pixels for the image in Figure 12.

Figure 14. Test 1 percentage of correctly classified crop pixels for the image in Figure 12.

Figure 15. Test 1 percentage of misclassified pixels for the image in Figure 12.

Block Based Error Evaluation

Perfect pixel by pixel classification is not necessary for site-specific chemical application. A practical approach would be to make a spray/not spray decision for blocks the size of the area covered by a small burst from a single nozzle tip. The block-based method does not require that every single pixel of the weed be identified in the block, but only that a sufficient number of weed pixels be classified correctly in order to effect a control decision. A threshold number can be set so that if the number of weed pixels exceeds that number it can be assumed that a weed exists in that block. This introduces the need to determine the threshold value that is the optimum for a given area. This threshold is probably dependent on the background, ambient lighting, size and age of the plants, the field of view, image resolution, and block size. The sizes used for this work were 1, 2, 4, 5, and 8-inch (2.5, 5, 10, 12.5 and 20 cm) blocks. Tables 2, 3 and 4 show the block evaluation results of the neural network weed detection accuracy. To obtain these values it was first necessary to evaluate all 16 single image series under different block sizes and thresholds. After this was performed, the results for a given block size and threshold were averaged across all

images for each wavelength calculation. Finally, since there was not a great deal of difference between some wavelength combinations, the results for each wavelength combination for a given block size and threshold were averaged together to yield the tabulated results. The three tests were kept separate to determine which setup gives the best results. The number of thresholds tested as well as the values of thresholds increased as the block size was increased.

Simulation Results

When spraying *small* stains, the flat nozzle is more efficient than the conic nozzle (Table 5). For example, at band size of 0.5 m the IFF is 1.88 for the flat nozzle as compared to 6.83 for the conic nozzle. The wider the spraying cut the lower the efficiency. For the flat nozzle, the efficiency decreases linearly and for the conic nozzle the decrease is approximately exponential (Figure 16).

For *large* stains, spraying with a flat nozzle is also more efficient (Table 5) but the difference between the flat nozzle and the conic nozzle is quite small (Figure 17). If we take for example the same band size of 0.5 m for the small stain, the IFF is 1.05 for the flat nozzle and 1.48 for the conic nozzle.

The influence of the detection level is negligible (Table 6). The IFF value for different detection levels are almost identical. For example, for a band size of 0.5m by using a conic nozzle the IFF is 1.64 for detection level of 50%, 1.66 for 70% and 1.66 for 90%.

Results indicate that site-specific spraying can decrease the amount of required chemicals substantially - up to 90%, depending on the proportion of the infected area. By using a conic nozzle for an infected field at 5%, the IFF for 0.5m band-width is 1.48. The required spraying area is 7.4% from the field and the approximate savings is 92%.

Table 5: The average ratio between the spraying areas and the stain areas (IFF) according to the nozzle type (flat or conic) and nozzle size

Small Stain (0.3 - 1 m)		Medium Stain (1 - 2 m)		Large Stain (4 - 6 m)		Band Size (m)
Nozzle Type						
Flat	Conic	Flat	Conic	Flat	Conic	
1.0914	1.7437	1.0276	1.3020	1.0047	1.0853	0.10
1.2609	2.7289	1.0784	1.6631	1.0134	1.1780	0.20
1.4690	3.9233	1.1421	2.0674	1.0245	1.2758	0.30
1.6983	5.3589	1.2217	2.5219	1.0377	1.3775	0.40
1.8866	6.8346	1.3146	3.0325	1.0523	1.4852	0.50
2.0741	8.5716	1.4158	3.5851	1.0681	1.5995	0.60
2.2674	10.5490	1.5236	4.1737	1.0858	1.7163	0.70
2.4362	12.5188	1.6274	4.7794	1.1050	1.8378	0.80
2.6225	14.7583	1.7318	5.4404	1.1252	1.9616	0.90

Table 6: The average ratio between the spraying area to the stains area (IFF) for stains size from the complete range (0.3 - 6 m) and for different detection level probabilities of the identification system.

Identification Level						Band Size (m)
90%		70%		50%		
Nozzle Type						
Flat	Conic	Flat	Conic	Flat	Conic	
1.0072	1.1100	1.0071	1.1100	1.0068	1.1082	0.1
1.0210	1.2336	1.0207	1.2351	1.0209	1.2332	0.2
1.0365	1.3600	1.0368	1.3583	1.0365	1.3576	0.3
1.0806	1.6582	1.0798	1.6611	1.0779	1.6438	0.5
1.1011	1.8058	1.1059	1.8346	1.1080	1.8338	0.6
1.1618	2.1632	1.1569	2.1617	1.1660	2.1962	0.8
1.1883	2.3376	1.1938	2.3799	1.1856	2.3337	0.9
1.2793	2.8985	1.2792	2.9265	1.2810	2.9171	1.2

Table 7: The average ratio between the spraying areas and the stain areas (IFF) from the *complete range* (0.3 - 6 m) according to the nozzle type (flat or conic) and nozzle size

Band Size (m)	Nozzle Type	
	Flat	Conic
0.10	1.0070	1.1087
0.20	1.0207	1.1234
0.30	1.0372	1.3644
0.50	1.0802	1.6611
0.60	1.1053	1.8236
0.80	1.1576	2.1571
0.90	1.1898	2.3503
1.20	1.2862	2.9506

Figure 16. Inefficient index for conic nozzle and flat nozzle for *small* stains (0.3 - 1 m)

Figure 17. Inefficient index for conic nozzle and flat nozzle for *large* stains (3 - 6 m)

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Evaluation of the research achievements

The technologies developed by this research effort demonstrate that site-specific chemical application is a practical alternative to conventional technologies. Multi-spectral reflectance characteristics of plants can be used to detect most weeds. Machine vision hardware is capable of digitizing and processing images in real-time. Neural networks can be trained to perform the pattern recognition necessary to distinguish weeds from crops. Studies of the spatial patterns of weeds show that the percentage of chemical saved by site-specific application increases as the size of the control block (minimum area to spray) decreases. The practical limit on the size of the control block depends on the nozzle and control technologies. The knowledge gained in this research effort, when coupled with advances in digital signal processing and micro-electronics and controls, should permit significant improvements in the efficiencies of agricultural chemical application.

Description of the cooperation

An extraordinary large number of faculty and institutions made significant contributions to this research. At Purdue, the collaboration included faculty from Agricultural and Biological Engineering, Electrical and Computer Engineering, Botany and Plant Pathology, Entomology and Horticulture. In Israel, contributions were made from Interdisciplinary Studies Department, Faculty of Engineering at Tel-Aviv University; Institute of Agricultural Engineering, ARO, Volcani Center; and the Department of Industrial Engineering and Management, Ben Gurion

University. A total of 14 faculty and graduate students worked on some aspects of this project. This does not include the technical staff and assistants.

V. Alchanatis and A. Hetzroni at the Volcani Institute joined forces with L. Ridel and L. Yaroslavsky at the Tel-Aviv University to develop statistical pattern recognition software for rapidly detecting weeds. Images collected at Purdue University were made available via the WWW site.

Cooperation included numerous exchanges via email and use of the World Wide Web. The multispectral images collected at Purdue were made available to colleagues at other institutions. The URL for the image collection is:

http://danpatch.ecn.purdue.edu/~agvision/Tiff_images/Contents.html

In addition, courtesy accounts were provided on the ABE computer network for research colleagues in Israel.

Conclusions

This effort has shown that site-specific application could reduce the amount of chemical required to control weeds and is technically feasible today. Studies show that the quantity of chemical potentially saved via site-specific spraying increases as the minimum decision area decreases. Multi-spectral imaging, combined with statistical pattern recognition or neural networks is capable of detecting weeds in real-time on relatively modest hardware. Image sensors with imbedded filters for the desired wavelengths, when integrated with digital signal processing (DSP) chips programmed to extract the desired features and detect weeds would make this technology practical and affordable.

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