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Role of Embedded System in Agricultural Equipments (A Review)

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Abstract

Embedded systems are microchips containing software that is "burned into" the chip. Embedded systems include devices used to control, monitor or assist in the operation of equipment, machinery or plant. Artificial neural network (ANN) based models have been explored for use in various agricultural machinery applications. The typical application has been based on Multiple Input / Single Output ANNs which can be used to model linear and non-linear surfaces. These types of models may be effective where response surface modeling has been used in the past. The capabilities of ANNs with respect to configuration, adaptation, noise tolerance, and training are addressed. In addition, the use of ANN models in embedded systems is discussed. Combine harvesters, Weed detection in sprayers, blueberry Bush pruning, weed identification, Grain elevator and Precision agriculture are discussed.

Keywords: *Artificial Neural Network, Harvesters, modeling, embedded system*

1. Introduction

Embedded systems often referred to as embedded chips, are one of the real unknowns related to Y2K issues. The real challenge for all sectors in a community is locating embedded systems because they exist in a wide variety of products. For example, from the most sophisticated manufacturing automation process to a simple VCR. The purpose of this fact sheet is to become familiar within the embedded systems, and ways to locate and remediate embedded system problems.The advent of microprocessors has opened up several product opportunities that simply did not exist earlier. These intelligent processors have invaded and embedded themselves into all fields of agriculture. As the complexities in the embedded applications increase, use of an operating system brings in lot of advantages. The use of an embedded system simplifies the design process by splitting the application code into separate tasks.

2. Artificial Neural Network

Potential applications of this type of ANN in machinery applications include predicting:

- Spatial yield response in fields in precision farming applications (Drummond, 1995).
- Machine performance, e.g. combine harvesters (Hall, 1992).
- Plant characteristics from sensor signals (Stone, 1994a; Zheng et al., 1994).
- Temporal dynamics in control systems (Altendorf, 1993).

3. Weed Detection in Sprayers

An ANN was developed to allow color patterns to be recognized in an agricultural weed sprayer application by Stone, (1994a). The structure of the most successful network tested is shown in Fig 1.

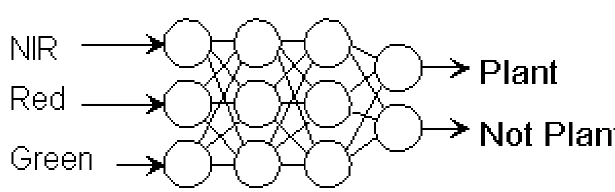

Fig1. Plant Color Recognition Model - Stone 1994a

Fig 2 presents a schematic of the sensor and spray nozzle element component of the sprayer. The complete sprayer consisted of many of the sensor-nozzle elements placed in parallel on a single spray boom.

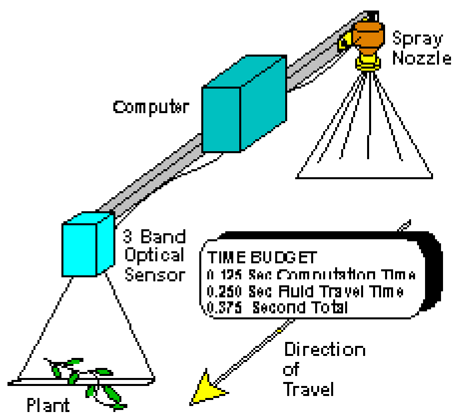

Fig 2 Sprayer Sensor and Nozzle Element.

A sensor was fabricated to detect color on the surface of the ground in a 7.5 by 50-cm wide image. Three color bands; green, red, and near infra-red were sensed. The signals from the sensor were digitized with a 68HC11 based controller using the on-chip 8-bit A/D converter. The 68HC11 based computer was also used to activate a solid-state switch that energized a solenoid valve in the spray nozzle. The intent of control in the system was to sense the presence of a weed by color and to activate the nozzle to spray the plant at the point in time that the plant was under the nozzle. A time budget is shown in the figure. If computing time plus the time required for the fluid to reach the ground once it emerges from the nozzle was insignificant, the sensor and nozzle could be located together. The 0.25 second time period between when the fluid emerges from the nozzle and when it reaches the ground cannot be changed. The configuration of the system places a practical limit on computing time. For a sprayer traveling in the field at 3 m/s, a typical ground speed, separation between sensor and spray nozzle must be 1.1 meters. This physical separation is near the maximum limit practical for the machine.

Agricultural sprayers based on optical sensing and control of spray nozzle activation currently exist on the market. The current designs rely on look-up table based models. This approach limits the number of inputs that can be practically used in the controller. A look-up table with three or more variables and with 8 bit precision will not fit conveniently in a low-cost micro-controller memory. An alternative to a look-up table is to encode the necessary response into an equation. Determination of a simple equation to model the problem is not a simple task.

Many potential interferences exist in detecting the plant, including: amount of target plant in the image, light level, dead plant matter, many soil colors, and variation in the color of the target plant. The inteferences result in an unusual map of sensor response based on color inputs. A non-linear model of some type is necessary. An ANN appeared to be a suitable model for the problem.

Training data were created by exposing the sensor to many different conditions intended to span the possible conditions that would be seen in actual application of the system. Soils of different colors were collected from six locations in Oklahoma. The soils were exposed to the sensor, dry and wet. In addition, various percentages of plant cover including 0%, 10%, and 100% were placed on the soils. In addition, the system was tested under various natural lighting conditions from heavy overcast to bright. Early testing revealed that in-door conditions could not easily be made to model out-door lighting. All combinations of the input conditions were tested resulting in nearly 80 sets of training conditions. The tests were repeated with similar conditions resulting in nearly 80 sets of test conditions that could be used to determine the performance of the system. Lighting, and plant placement could not be repeated exactly, resulting in significant variations between the test and training data.

Neural networks with one and two hidden layers were tested with different numbers of nodes in each layer. Table 1 presents results of training different configurations. The table presents the performance of the model after training on the training data and evaluation of errors that were found comparing model predictions of the test data. Two types of errors were computed to evaluate performance of the model. they were percentage of tests where the plant was present and detected (Plant % correct), and the percentage of tests where the plant was not present and not detected (No Plant % correct). Many more training iterations were performed, but are not shown. The table presents only tests where the "% correct when the plant was present" was maximized. For the current application of the sprayer, it is much more important to assure a plant has been sprayed than to avoid spraying when unnecessary. Current sprayer designs operate continuously and would have values of 0 and 100% for the "No Plant % Correct" and the "Plant % Correct" performance measures.

Table 1. Performance of network configurations

Nodes in Hidden Layer 1	Nodes in Hidden Layer 2	No Plant % Correct	Plant % Correct	Epochs
3	2	75	90	85000
3	3	80	92.5	60000
4	4	70	92.5	55000

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5	5	70	92.5	55000
6	6	70	92.5	50000
7	7	65	92.5	70000
8	8	75	90	55000
3	0	45	100	20000
4	0	45	97.5	20000
5	0	50	100	20000
6	0	50	100	30000
7	0	40	100	25000
10	0	92.5	70	20000

Models with a single hidden layer in general were able to detect plants but were not as effective at rejecting situations where no plant was present. The training "epochs," the number of cases for which the network was optimized for ranged between 20,000 and 85,000. As expected, the number of epochs required to optimize the single hidden layer model was less than the two layer models. Training was done on a SUN IPX workstation using NeuralWare'sNeuralWorks Professional II/Plus neural network development package. Training required 2 to 5 minutes for each configuration.

The model described in the second entry in Table 1 with three nodes in each of two hidden layers was selected for use in the prototype sprayer. More complex models did not improve the accuracy, and the single layer models were judged to have too large an error when no plant was present. The less complex model also allowed faster executing and smaller code to be used in the embedded application.

The resulting model was coded in C, compiled, and placed in the micro-controller. Two approaches were used to develop the code for the application. NeuralWare's developers package, DPACK, was used to automatically convert the network description into C. Additionally, the network was hand coded in C using equation 1. Table 2 presents code size and execution times for different optimizations of the embedded code.

Several techniques were tested to reduce the execution time of the code. The hand-coded version of the model was converted to a look-up table rather than the C function htan(x). The look-up table increased code size but reduced execution time by more than 50%. An alternative activation function, $f(x) = 1/(1-x)$ was also tested and compiled in a floating-point form. The model had to be retrained using the alternative activation function with the same results as the originally selected activation function, $f(x) = \text{htan}(x)$. The look-up table based model performed better than using $f(x) = 1/(1-x)$ coded in floating point. Finally, the whole implementation of the model in C was coded in integer arithmetic. Some components of the calculation required double precision integers to retain accuracy. The resulting code produced an output in 0.07 seconds, after supplying inputs. This computational speed permits the time budget presented in figure 4 to be met and allows a feasible geometry for the physical components of the system.

Table 2. Execution time and code size for the production model

Model Description	Arithmetic	Activation Function	Code Length (Bytes)	Execution Time (s)
DPACK1 generated	Floating Point	Floating Point, $f(x) = \text{htan}(x)$	36K	-
Hand Coded	Floating Point	Floating Point, $f(x) = \text{htan}(x)$	3.5K	0.3
Hand Coded	Floating Point	Floating Point, $f(x) = x/(1-x)$	3.5K	0.15
Hand Coded	Floating Point	Look-Up Table, $f(x) = \text{htan}(x)$	3.8K	0.13
Hand Coded	Integer	Look-Up Table, $f(x) = \text{htan}(x)$	3.5K	0.07

Some degradation in the accuracy in detection of plants was expected when the model was converted to look-up tables and integerized. Testing of the resulting models on the original test data revealed no significant difference between the integerized model and the original floating point model.

A prototype sprayer using nozzle elements based on the design was tested in the field. Though performance of the prototype was consistent with initial testing of the model, field tests revealed several unexpected operating limitations. The sensitivity of the prototype detectors was greatly diminished under low light conditions. Training of the model was not done under light conditions as low as those experienced in the field. In addition, during dawn and dusk periods, the color of the natural light is shifted toward red. Both conditions resulted in reduced sensitivity.

4. Blueberry Bush Pruning

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Zheng and Rohrbach (1994) reported the development and testing of an ANN which would process ultra-sonic distance measurements to determine plant position. They

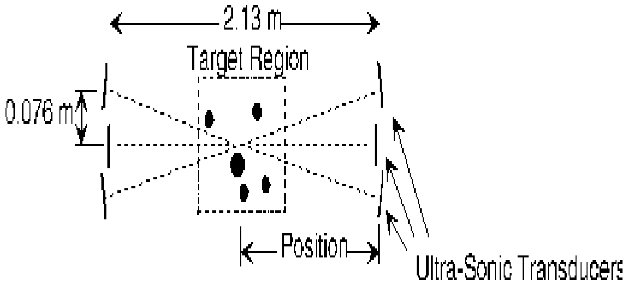


Fig 3. Bush Ultra-Sonic Sensor Arrangement - Zheng and Rohrbach - 1994

designed an array of 6 ultrasonic range finder devices which were focused towards the center of a target blueberry plant as depicted in Fig 3.

The purpose of the resulting system was to position a trimming apparatus to trim branches from the blueberry plant. The ultra-sonic transducers were set to sense the closest branch intercepted by the sound beam for a

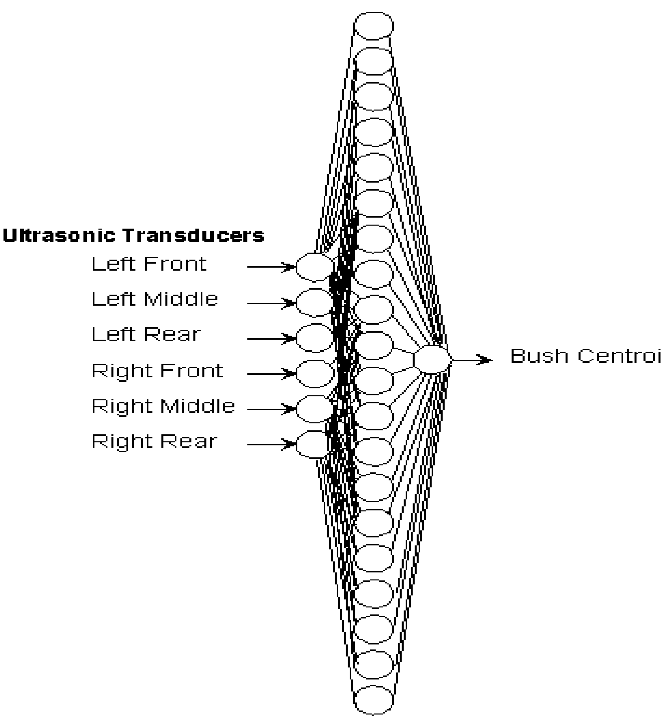


Fig 4. Bush Centroid Prediction - Zheng and Rohrbach - 1994

particular sampling. A 6-20-1 configuration of an ANN was trained to use the distance measurements from the ultrasonic transducers and to predict the center position of the target plant, as shown in Fig 4.

A total of 343 cases were collected and divided, with 75% of the cases used for training and 25% used to test and compute error for a combined model. Of that total, 269 of the cases were taken with a single plant stem target and 74 cases with multiple stem targets. The ANN was trained until the test dataset MSE was minimized, A total of 343 cases were collected and divided, with 75% of the cases used for which required slightly more than 300,000 epochs (number of times cases were individually presented to the network.). A second network configuration consisting of three 6-20-1 networks was also tested. One of the networks was used only to determine distance for cases with a single stem, another to determine distance for cases with multiple stems, and a third network was used to classify cases as single or multiple stems. The strategy is depicted in Fig 5.

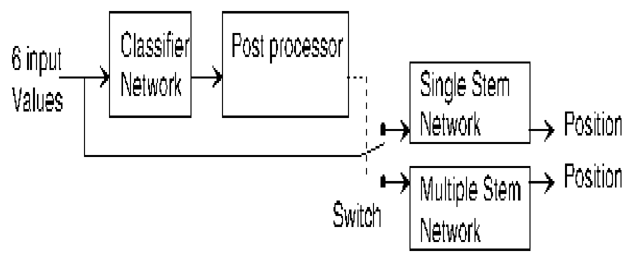


Fig 5. Modular network design - Zheng and Rohrbach - 1994

This configuration of the network required less than half the training time, while producing slightly less error in the predicted position. Training time was an issue with the software and problem combination presented here, taking 4.3 hours on a DEC 5000/25 computer. The authors estimated the training could have been shortened to slightly over an hour on a Cray Y-MP super-computer. Standard deviations of the position errors produced by both configurations of networks were approximately 0.008 m and were distributed with a central tendency.

5. Weed Identification

Zhang et al. (1994) reported the use of ANNs to process color images of weeds in a winter-wheat environment with the objective of being able to distinguish between weeds and other components of the image. They were particularly interested in detecting weeds with reddish stems. They initially attempted to apply a 6-10-5 network to process 6 spectral indices and classify the inputs into five classes; weed stem, leaf, soil, cracks and shadows, and stones and bright spots. They were unsuccessful in training the network to acceptably classify the image. A second configuration, a 48-24-5 network configuration as shown in Figure 7 was tested.

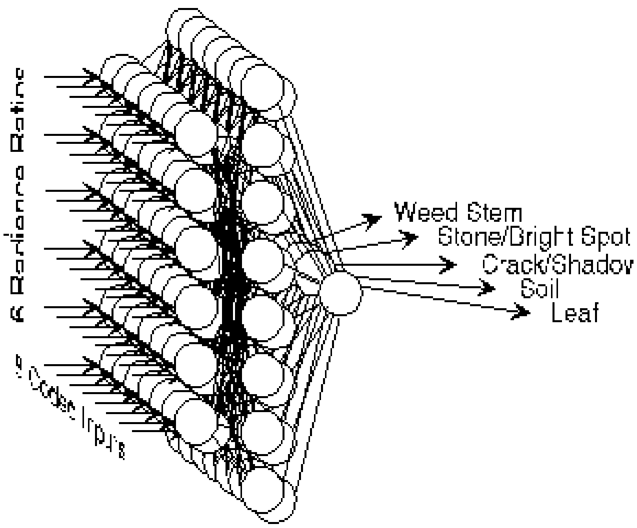


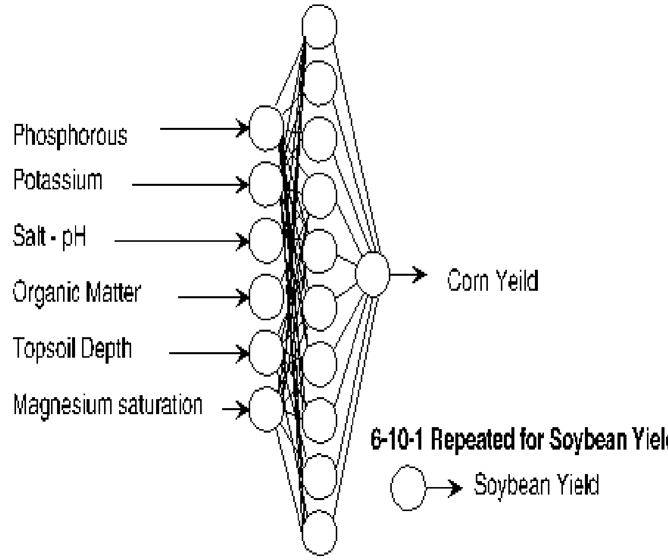
Fig 7. Image Classification - Zhang et al. - 1994

The input spectral indices were coded as 8-bit values with one input for each bit of the index. This resulted in 6 indices x 8 bits or 48 inputs which had 1 or 0 values. Six hundred pixels taken from three images were pre-classified and used to form training and testing data sets. The trained network was then tested on six images, three originally containing the training data and three additional images.

The ANN was compared with a discriminant analysis approach to classifying pixels in the images. The ANN approach was not successful in classifying images of weed varieties different from the wild buckwheat images of the training data. The ANN did perform well on images similar to the training data. Overall error rates where test data sets were different from training data sets were slightly under 40%, while overall error rates for discriminant analysis were slightly less than 30%. In this study, ANNs did not perform better than a conventional approach. The authors did not report efforts to optimize the ANN to improve performance.

6. Modeling Variability in Fields

Drummond et al. compared the performance of three different types of multivariate modeling techniques for use in predicting crop yield. Soil fertility was sampled on a 30-m grid and top soil depth was measured with a finer



resolution using a soil conductivity meter. Yield was measured for two crops; corn, grown in the field in 1993, and soybeans grown in the field in 1994. Yield was measured at one-second intervals during harvest on the combine harvester with a yield monitor and position measured with a GPS unit. The spatial resolution of the combine data were not reported, but is estimated here at approximately 2 m in the direction of travel and 6 m across the direction of travel. The instantaneous yield was corrected in position for delay through the combine harvester. Both the yield data and the soils data were kriged to a 10 m grid. A 25-ha field was sampled, resulting in a 2576-point data set. The data were randomly divided into training and testing data sets for the neural network development, but the r2 results are reported for the combined dataset. The network geometry used is shown in Fig 6. Experimentation with other geometries was not reported.

Fig 6. Yield Prediction Model - Drummond et al. 1995

The authors reported that the training did not result in overfitting, based on comparisons of the results on the training and testing data sets. Further, additional training in the 1993 data set may have resulted in higher r2 but was not done to retain consistency with the 1994 data set. Table 3, taken from Drummond et al. (1995) compares the performance of the different modeling techniques.

The authors concluded that weather variations were potentially the major cause of un-explained variability in the modeling. In addition, they also concluded that some further un-explained variability may have been due to non-weather related factors not included in the models. Measurements of soil nitrogen levels or nitrogen application was not reported in the study.

Table 3. Goodness-of-fit for yield prediction for various modeling techniques (Drummond et al., 1995)

Model	1993 Yield Estimation		1994 Yield Estimation	
	r2	Std. Error (Mg/ha)	r2	Std. Error (Mg/ha)
Multiple Linear Regression	0.21	1.20	0.42	0.26
Stepwize Multiple Linear Regression 9 soil parms., 6 best terms	0.23	1.19	0.43	0.26
Stepwize Multiple Linear Regression 6 soil parms.+ interactions, Sig. terms	0.27	1.16	0.57	0.22
Partial Least Squares Regression 6 soil parameters	0.21	1.20	0.41	0.26
Projection Pursuit Regression 6 soil parameters	0.57	0.88	0.73	0.18
ANN 6 soil parameters	0.54	0.94	0.67	0.19

7. Precision Agriculture

Precision agriculture is a new agriculture technology system development quickly in recent years. Integrating agronomy, geography, biology, agrology, botany, geo-spatial science, and precision agriculture can be defined as a comprehensive system designed to help farming. It involves various problems in crop planning and includes tillage, planting, chemical applications, harvesting, and post harvest processing of the crop. Precision farming is a pro-active approach that reduces some of the risk and variables common to agriculture so we think that it has the potential of optimizing cost and ecological effects through the application of crop information, advanced technology and management practices. Accordingly, how to get these information and data quickly and accurately becomes the foundation of precision agriculture construction, while how to manage the information and make decision quickly and intelligently is the key technology in precision agriculture.

It is obvious that information technologies are foundation of precision agriculture, and positioning, timing, mapping and analysis are most important among them. Accordingly Mobile Mapping System can help agriculturist with a new capability of gathering information for implementing decision-based Precision Agriculture.

7.1 Improve the Accuracy of Soil Sampling

Soil conditions and soil quality influence crop growth greatly. Usually how often do farmers fertilize the soil or water the land depends on the soil conditions and plant type. So it is a basic work to master the soil conditions. From the view of precision agriculture soil is different meter by meter. Thereby soil sampling becomes the foundation step. The accuracy of soil sampling is requested higher. Accuracy of soil sampling refers mainly to accurate degree of the position information where the soil samples were taken. With the accurate knowledge about the coordinate location of the soil samples, a soil data layer can be developed accordingly. With the accurate position information, navigating back to those locations for re-sampling is possible.

Mobile Mapping System has equipped navigation sensors, such as GPS and INS, so the time and position information can be recorded at the same time when soil samples are taken. Consequently a soil difference map can be create, on which physical attribute of soil is described.

7.2 Plant Growth, Diseases and Insect Pests Monitor

Generally precision agriculture is constructed in a large area. Hereby it is impossible for all plants growing in like manner. Sometime only a single part suffers the diseases and insect pests. Then it is unnecessary and even harmful for all plants to spray pesticide or other medicine in the same way. Different solution should be taken according to the real conditions of plants.

Mobile Mapping System can finish the monitor task of all the plants. Using the scanners, the peculiar plants can be found quickly, and its position also can be recorded. In fact satellite remote sensing data also can provide such distinction information. Compare with Mobile Mapping System, its spatial range is much larger but space resolution is lower and constrained by satellite calendar.

7.3 Analysis of the Crop and Field Information

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The purpose to get so much data about the soil, plant and so on is to master the planting conditions and to make decisions for all planting process. Accordingly GIS and Agriculture Expert System are usually imported in precision agriculture in order to edit, process, integrate and analyze the crop and field information and get corresponding resolve scheme.

Mobil**e** Mapping System may Load multi-source information and different types of agricultural data to master the conditions of the field. Comparing the information or data, relationships within and between data sets can be found. That is the relationships among different factors can be made certain. By the relation, agronomist or Agriculture Expert System can make production plan.After the production plan has been made, farmers can command the farming machines to work automatically, for these machines has been equipped intelligent implement and positioning devices. Moreover the entire process of one year farming also can be recorded and evaluated, and the experience can be analyzed to help next year work.

8. Conclusion

Five cases of application of the embedded systems in agriculture machinery are reviewed. The application and performance of models in each case were discussed. Some general conclusion can be drawn from the applications:

- Embedded systems also have its application with artificial neural networks.
- Embedded systems are allowed to the need for the effective speed and memory utilization.
- Artificial neural networks are an effective alternative to non-linear regression analysis in fitting surfaces.
- Precision agriculture with the help of embedded systems becomes more efficient, intelligent and steady.

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