Perceptron neural network to evaluate soybean plant shape

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ABSTRACT

In agriculture, human visual judgments take important roles. The visual selection on plant shape in breeding process is one example of such judgments. In this study, in order to develop a stable and generalized plant shape evaluator that can substitute for human visual judgments, we examined perceptron neural network system. We developed a three layers perceptron neural network simulator with direct image inputs. We examined the replacement with such the human visual judgments by the simulator. The matches between the simulator judgments and the human visual judgments, were approximately 60~80%. Though we also examined the relationship between the number of unites and the success rates, we were not able to find any relationship between them. We need to modify the network structure to obtain more appropriate judgments on plant shape.

1. Introduction

In agriculture, human visual judgments take important roles. Such judgments are, however, rather subjective and unstable. Therefore, the system that can substitute for such human empirical judgments has been being strongly required. The visual selection on plant shape in breeding process is one example of such judgments. Plant shape is important, because it has strong connections with final yield. That is, it functions on light perception of plant canopy, lodging resistance, etc.

Ninomiya *et. al.*[1] discussed three models (discriminant function, neural network, fuzzy logic) to evaluate soybean plant shape automatically. Those models were based on parameterized values extracted from image data such as plant width, height, silhouette area, and several statistical estimates on marginal frequency distributions of silhouette images of soybean. They showed that approximately 80% of the judgments by those models agreed with human visual judgments. Those models, however, require the parameterization of images. That is, we have to take difficult processes to find useful parameters for the judgments, when we develop new models for different plants. The lack of the robustness of the models has been also pointed out.

In this study, in order to solve those problems and develop a stable and generalized plant shape evaluator, we examined perceptron neural network system with direct image input where no parameterization of image data was necessary. The application of neural network in biological sciences is becoming popular. For example, Morris *et. al.*[2] and Balfoort *et. al.*[3] applied neural networks to identify basidiomycete spores and phytoplankton. We cannot, however, find any reports where input data to biological images themselves were directly used as networks.

2. Materials and Methods

We asked three expert soybean breeders to give the judgments (either "Good", "Fair" or "Poor") on the soybean plant shape using the same 877 binary images as Ninomiya *et. al.*[1] Among those images, 326 images for which the breeder's judgments agreed with each other were selected for this study. Figure 1 shows some examples of the soybean binary images. At this moment, our purpose is to develop a model whose judgments always agree with those experts' judgments.

Three layers perceptron neural network with direct binary image input was adopted. Therefore, the number of input units simply depended upon the image size. The original images with 256x256 pixels were scaled down to either 8x8, 16x16, 32x32 or 64x64 pixels as input images, because the original images were too huge to compute. The scaling down consequently made those images smoothed. We set -1 and +1 to white and black pixels on the binary images, respectively. The number of hidden units was set to be either 8, 16, 32 or 64 depending upon the experiments. The number of output units per output pattern vectors was set to be either three or six. In the case of three output units, the target output pattern vectors for "Good", "Fair" and "Poor" were (1, -1, -1), (-1, 1, -1) and (-1, -1, 1) respectively. In the case of six output units, the target output patterns were (1, 1, -1, -1, -1, -1), (-1, -1, 1, 1, -1, -1) and (-1, -1, -1, -1, 1, 1)

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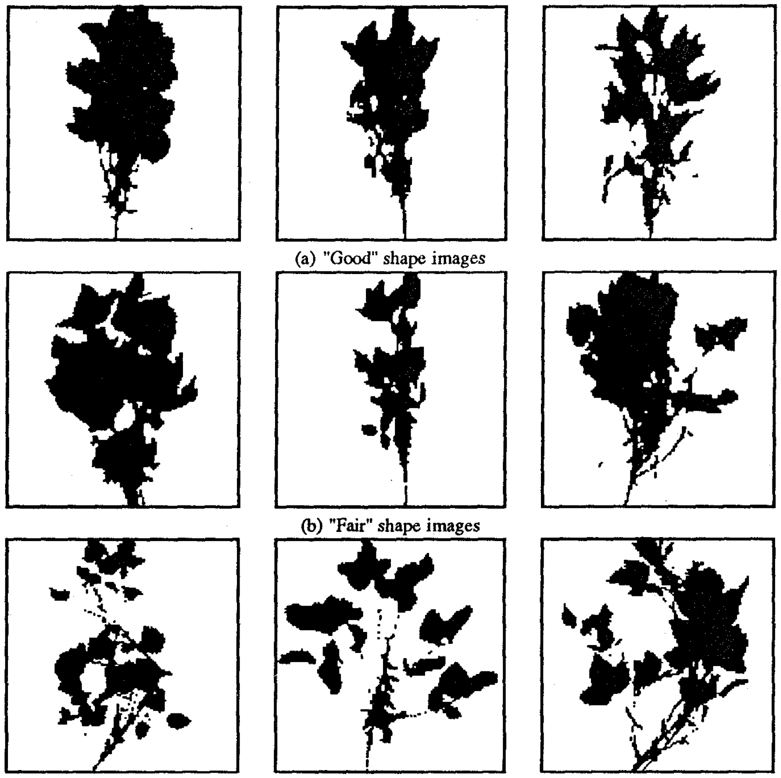


(c) "Poor" shape images

Figure 1 Examples of soybean plant shape

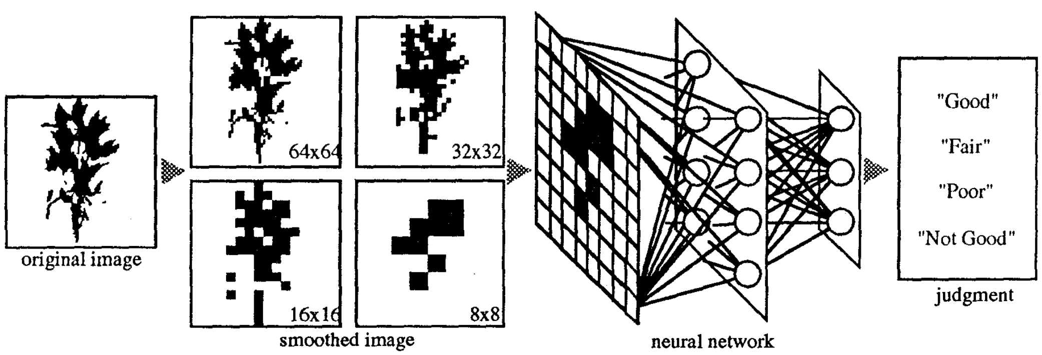


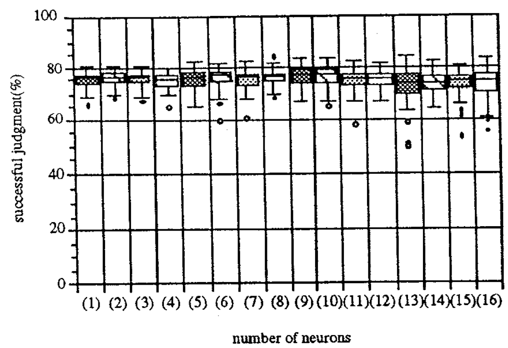
Figure 2 Schematic diagram of soybean plant shape evaluation by the neural network

respectively. Figure 2 shows the schematic design of this study. We defined that a judgment of the neural network is decided by an output vector element with maximum value when the neural network is tested. For example, when the output vector in the case of three output units is (-0.2, 0.9, 0.1), the judgment is defined to be "Fair", and when the output vector in the case of six output units is (0.8, -0.1, 0.2, -0.5, 0.3, 0.3), the judgment is defined to be "Good".

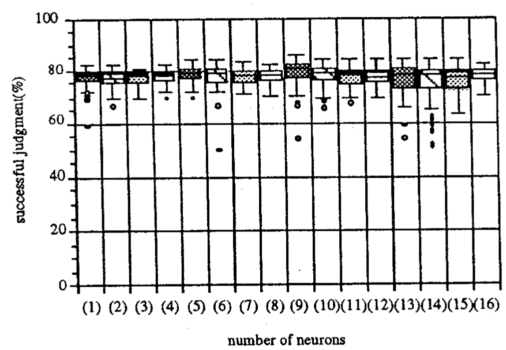
We applied the analog neuron model to each unit. In the other words, the relationship between inputs and an output of a unit can be expressed as follows:

$$y = \tau\left(\sum_{i=0}^{n} w_i x_i\right)$$

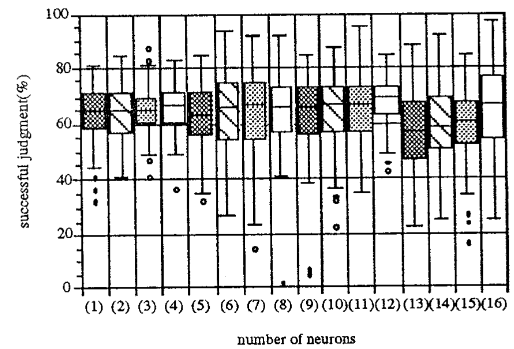
where n, $x_i(i=1,...,n)$, y and $w_i(i=0,...,n)$ are the number of inputs of a unit, the inputs of a unit, the output of a unit and the weights of synaptic links, respectively. We set x_0 to be one. $\tau()$ is the sigmoid function defined by



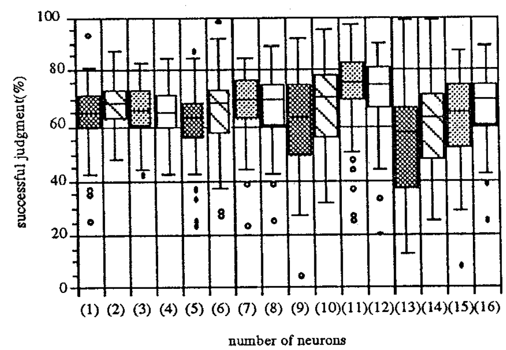
(a) Success rates of "All"(three output units)



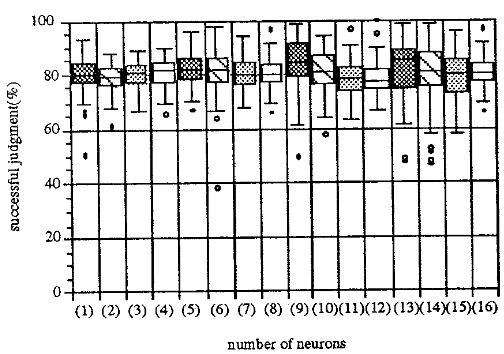
(b) Success rates of "All"(six output units)



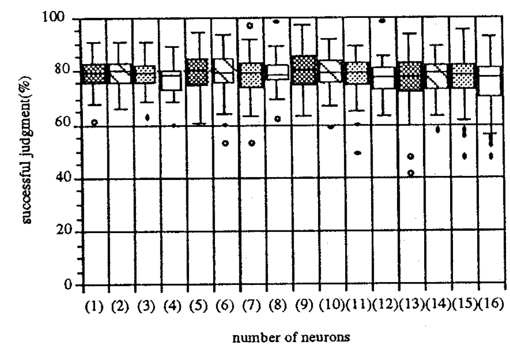
(c) Success rates of "Good"(three output units)



(d) Success rates of "Good"(six output units)



(e) Success rates of "Not Good"(three output units)



(f) Success rates of "Not Good"(six output units)

Figure 3 Success rates and effect of the number of units on judgment

Success rate of 100 times' trials for each network structure is shown. Boxes include 50% of data, bars in the boxes and circles indicate the median and the outliers, respectively.

(1) 8x8 input units, 8 hidden units
(2) 8x8 input units, 16 hidden units
(3) 8x8 input units, 32 hidden units
(4) 8x8 input units, 64 hidden units
(5) 16x16 input units, 8 hidden units
(6) 16x16 input units, 16 hidden units
(7) 16x16 input units, 32 hidden units
(8) 16x16 input units, 64 hidden units
(9) 32x32 input units, 8 hidden units
(10) 32x32 input units, 16 hidden units
(11) 32x32 input units, 32 hidden units
(12) 32x32 input units, 64 hidden units
(13) 64x64 input units, 8 hidden units
(14) 64x64 input units, 16 hidden units
(15) 64x64 input units, 32 hidden units
(16) 64x64 input units, 64 hidden units

$$\tau(u) = \frac{2}{1+e^{-u}} - 1.$$

Twenty-six training sample images that contained 7 "Good", 9 "Fair" and 10 "Poor" shape images, were chosen for back-propergating training. The selection of the training sample images was made visually based on typicality of their shapes. The weights of synaptic links were initialized randomly between -0.3 and 0.3. The training was continued while the mean square error between the output from the neural network and the target output was larger than 0.2. The training was repeated 100 times for each network structure. Then, each trained network was tested by the 300 images excepting the 26 training sample images from the 326 images.

The neural network simulator was originally developed with C language on HP9000/750(Hewlett-Packard, Inc., Palo Alto, California, USA).

3. Results and Discussion

Each training needed about 800 iterations and 1~200 minutes(depending upon the number of units) until the convergence of supervised learning. When a judgment by the neural network matched the breeder's judgment for the same image, the judgment was taken to a success. The distributions of the rate of the successful judgments are described in Figure 3. It shows the effect of the number of units on the judgments. We defined "Not Good" as a new judgment level by combining "Fair" and "Poor" judgments, because breeders select only "Good" shape plants in their breeding process. We defined following success rates:

Success rate of "All"=$(G_{succ}+NG_{succ})/(G+NG)$,
success rate of "Good"=G_{succ}/G
and success rate of "Not Good"=NG_{succ}/NG,

where G and NG are the number of "Good" and "Not Good" shape images, respectively, and G_{succ} and NG_{succ} are the number of successful judgments on "Good" and "Not Good" shape images, respectively.

The medians of the success rates of "All", "Good" and "Not Good" were approximately 75%, 65% and 80%, respectively. The success rates were about 10% lower than the former study[1]. It was shown that it was more difficult to judge "Good" shape correctly than "Not Good" shape. This result is, however, fairy good, considering that images were directly input to the neural networks without any parameterizations. As Figure 3 shows, the relationship between success rates and the number of units was not clear. At this moment, we have not found any reasons for it and it is the subject of the further study.

Several researchers suggested that neural networks worked for pattern recognition of comparatively simple images. Character recognition is a typical example. This study suggests that perceptron neural network is effective to judgment for rather complex images such as plant shape, though the success rate was not satisfactorily high in this study and we cannot apply our system to the actual breeding process yet. For the better success rate of evaluation on soybean plant shape by the neural network, we need to modify the network structure (the unit numbers, the input image size, the target output patterns, etc.). Moreover, we need to consider the selection method of training samples, because training samples decide the network structure and consequently affect the success rates profoundly.

4. References

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[2] Morris C. W., Boddy L. and Allman R.: Identification of basidiomycete spores by neural network analysis of flow cytometry data, Mycol. Res., Vol.96, No.8, pp.697-701(1992).

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