Plant Shape Discrimination of Several Taxa without Shape Feature Extraction Using Neural Networks with Image Input

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The importance of developing a quantitative shape discriminant method has been widely emphasized to obtain a consistent and objective evaluation. In fact, several methods for shape discrimination have been proposed. However, each of the methods can only be applied to a specific material, requiring specific shape features. Considering the number of shape discrimination problems in agriculture, such as genetic resource management, a single model that can be generally applied to different discrimination problems is highly desirable. A shape discriminant model based on neural networks with image input that did not require any shape features has been recently proposed, and it was shown that this model could be applied to soybean leaflet shape discrimination. This model was expected to be highly suitable for various materials, because it did not require any shape features. In this study, we examined the applicability of this model to the discrimination of several plant materials, by changing the training conditions of the neural networks to find their optimal combination. The plant materials were as follows: maple leaves, Tartary buckwheat kernels, pear fruits, mulberry leaves, and leaf-mustard leaves. The discriminant error rates, which were evaluated by cross-validation examination, differed depending on the materials, the number of training classes, and the training conditions. For example, the cross-validation error rate was 0.202 in the case of maple leaf shape with 10 training classes under the optimal training condition. The optimal training condition was common to all the materials examined in this study. Considering that this model did not require any shape features, its error rate was acceptable. This model can be widely and easily applied even for the evaluation of rather complex shapes such as lobed leaves. We concluded that this model would be highly suitable when various shapes of phytoorgans in many species have to be discriminated, such as in the case of genetic resource management.

Key Words: fruit shape, image analysis, kernel shape, leaf shape, neural network, shape discrimination.

Introduction

The shape of phytoorgans such as leaves, fruits, and kernels plays an important role in plant classification and identification for genetic resource management (Matsuoka 1989). Plant shape has traditionally been estimated by human visual judgment, though this method of evaluation is essentially inconsistent and subjective.

Several researchers have developed methods of quantitative evaluation of plant shape for consistent and objective results. For example, Guyer *et al.* (1993) and Wu (1994) showed that shape features (aspect ratio, area, etc.) could describe variations of leaf shape. Jensen (1990), McLellan (1990), Ray (1992), and Im *et al.* (1998) developed a leaf shape discriminant method based on landmarks. Travis and Draper (1985), Chen *et al.* (1989), Liao *et al.* (1993), Rigney and Brusewitz (1993), Ding and Gunasekaran (1994), Ghazanfari *et al.* (1996), and Ni *et al.* (1997) carried out classification or inspection of seeds using shape features (length, width, etc.). All of these previous methods required shape features, which were defined *ad hoc* for the specific material. Thus, these methods strongly depended on the materials, and did not seem to be applicable to other materials. This approach is inefficient, when various materials have to be discriminated based on their shape in the case of genetic resource management, for example.

On the other hand, Oide and Ninomiya (in press) proposed a shape discriminant model that did not require any shape feature definition. They directly inputted plant shape images to neural networks (NNs) in order to avoid defining shape features. They used a Hopfield model (HM, Hopfield 1982) and a simple perceptron (SP, Rosenblatt 1962), and applied them to soybean (*Glycine max* L. Merr.) leaflet shape discrimination, resulting in a sufficiently high predictability. Because this model did not require any shape features, they expected that the model would be generally suitable for other shape discrimination problems.

In this study, we examined the applicability of Oide and Ninomiya's (in press) model by employing it in other discrimination tasks, such as maple (*Acer* spp.) leaf shape, Tartary buckwheat (*Fagopyrum tataricum* Gaertn.) kernel shape, pear (*Pyrus communis* L. var. *sativa* DC) fruit shape, mulberry (*Morus* spp.) leaf shape, and leaf-mustard (*Brassica juncea* Czernjew et Cassor) leaf shape.

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Materials and Methods

Plant materials

We used the following plant materials: a total of 278 individual leaf shapes of 14 maple species, a total of 800 individual kernel shapes of 40 Tartary buckwheat varieties, a total of 207 individual fruit shapes of 11 pear varieties, a total of 188 individual leaf shapes of 10 mulberry varieties within 4 species, and a total of 353 individual leaf shapes of 30 leaf-mustard varieties. In the case of maple leaf, specific discrimination within a genus was performed. In the case of mulberry leaf shape, varietal discrimination within a genus was performed. In the cases of Tartary buckwheat kernel, pear fruit, and leaf-mustard leaf shape, intra-specific discrimination was performed.

For the analysis of the Tartary buckwheat kernel shape and the leaf-mustard leaf shape, the data described by Yoshida *et al.* (1995) and Kitaura *et al.* (1997) were used, respectively. The maple leaves and mulberry leaves were photocopied, then the images of the copied leaf shapes were taken by video camera. The pear fruits were put on a table with a light source, and the images of their side silhouettes were taken by video camera from above.

The results were compared with those from the study of Oide and Ninomiya (in press), in which this model was applied to the discrimination of a total of 364 individual leaflet shapes of 38 soybean varieties.

Contour standardization

The contours of the materials were described with the standardized elliptic Fourier coefficients (Kuhl and Giardina 1982, Furuta *et al.* 1995) so that shapes were independent of the size, rotation and translation. The standardization of the contour data for input to the NNs played an important role in this study. Since it was considered that the NNs may identify the same shape in a different orientation or position as a different shape, we solved this problem by introducing the standardized elliptic Fourier descriptor. The evaluation was independent of the size, rotation, and translation; that is, the model could evaluate the materials purely based on their shapes. We obtained individual shape images by filling in the contours drawn with the standardized elliptic Fourier coefficients (Fig. 1).

Examination using neural networks with image input

In order to verify the wide applicability of the model, we repeated the process of examination of the model after changing the materials; that is, we trained the NNs under several combinations of conditions, then introduced the individual shape images as test data to the trained NNs in order to obtain the discriminant error rate. We examined the following aspects: (1) the number of training classes that the NNs could learn; "class" refers to species in the case of maple leaf, and variety in the case of Tartary buckwheat kernel, pear fruit, mulberry leaf, leaf-mustard leaf, and soybean leaflet, (2) the optimal combination of training condi-

Fig. 1. Examples of supervisor and test images. The gray-scale image corresponds to the shape distribution image for the supervisor data, and the five binary images are the sub-set of the individual shape images used as supervisor images. Variation within a class was shown. (a) Maple leaf shape, (b) Tartary buckwheat kernel shape, (c) Pear fruit shape, (d) Mulberry leaf shape, (e) Leaf-mustard leaf shape, (f) Soybean leaflet shape.

tions, and (3) the discriminant error rate for each material.

Number of training classes that the neural networks could learn

We first examined the number of training classes that the NNs could learn, starting with two training classes, and increasing the number to five, 10, ..., up to the number of all classes. More dissimilar classes were used earlier in the training process; that is, we selected the training classes so that the sum of the square of the dissimilarity between each training class was maximized. The dissimilarity between classes was defined as the difference between the averages of the first principal components of the standardized elliptic Fourier coefficients of the individual shapes within a class.

Optimal combination of training conditions

Supervisor data were the set of the input images and the target output used to train the NNs. In this study, these consisted of the mean shape and the shape distribution images. The mean shape was defined as a filled contour

drawn with the averaged standardized elliptic Fourier coefficients of the individual shapes within a class. The shape distribution was defined as an average image where the intensity of each pixel was the mean of the intensity of each pixel of the individual shape images within a class. We examined three different image sizes as input data: 16×16 , 32×32 , and 64×64 pixels, respectively.

Two types of NN architecture were examined in this study: the HM and the SP types. The HM in this study consisted of the same number of linear units as the pixel-number of an input image (Fig. 2a). The HM was trained to work as an associative memory. The SP in this study consisted of an input and output layer on which linear units were arranged (Fig. 2b). In this model, the number of input units was the same as the pixel-number of an input image, and the number of output units was the same as the number of training classes. The SP was trained to map the supervisor images onto the target output vectors.

In order to examine the dependence of the learning efficiency and discriminant error rates on the training conditions, we trained the NNs under every combination of NN architecture (either the HM or the SP), supervisor images (either the mean shape or the shape distribution images) and image size (either 16×16 , 32×32 , or 64×64 pixels).

Discriminant error rate

We examined two types of discriminant error rate: the fitting error rate and the cross-validation (CV) error rate. The fitting error rate was defined as the discriminant error rate from NNs trained with the supervisor data based on all the individual shape contour data within the training classes. We used all the individual shape images within the training classes as test data. The CV error rate was defined as the discriminant error rate from CV examinations. CV examinations were carried out as follows. We used an individual shape image as test data and compiled the rest as supervisor data. After we trained the NNs with supervisor data, we determined whether the NNs could identify the training class of the remaining individual shape images. We repeated this operation until each individual shape image was selected as test data once, and finally calculated the discriminant error rate by combining the identification results.

Results

The NNs could learn all the training classes of each material under all combinations of training conditions except in some cases of training conducted with mean shape images of 16×16 pixels. The combinations under which learning failure occurred are shown in Table 1. Learning failure occurred when the neural networks underfit the supervisor data; that is, the supervisor images were not linearly independent.

The SP could complete discrimination of the test data faster than the HM. SP discrimination was performed in a single step, whereas HM discrimination required iteration

(a)

(b)

Fig. 2. Structure of neural networks. N indicates the pixel-number of the input images and P indicates the number of training classes. (a) Hopfield model (HM), (b) Simple perceptron (SP).

until a stable equilibrium was reached.

The fitting error rates differed depending on the combinations of training conditions, even within a material. The fitting error rates were lower with the SP than the HM; with the shape distribution than the mean shape; and with the 32×32 and 64×64 pixel-images than the 16×16 pixel-images. Consequently, the SP trained with a shape distribution of 64×64 pixels showed the lowest fitting error rate. The CV error rates strongly depended on image sizes within a material, and were lower with the 32×32 and 64×64 pixel-images than with the 16×16 pixel-images. The effect of the NN architecture and supervisor images on the CV error rates seemed to be less conspicuous than that of image

Table 1. Combinations of training conditions under which learning failure occurred

Material	Number of training classes	Neural network architecture	Supervisor image	Image size (pixels)
Maple leaf	More than 5	Both HM and SP ¹⁾	Mean shape	16×16
Tartary buckwheat kernel	More than 10	Both HM and SP	Mean shape	16×16
Mulberry leaf	More than 5	Both HM and SP	Mean shape	16×16
Soybean leaflet	More than 30	Both HM and SP	Mean shape	16×16

¹⁾ HM and SP are abbreviations for Hopfield model and simple perceptron, respectively.

sizes. Generally, the larger the number of training classes, the higher both types of discriminant error rates.

We carried out an analysis of variance to determine whether the fitting and CV error rates varied with the training conditions. In this analysis of variance, we used only 2, 5 and 10 training classes, because the maximum number of classes was 10 in the case of mulberry leaf. The analysis of variance showed that the main effects of materials, the number of training classes, NN architecture, supervisor images, and image sizes on the fitting and CV error rates were significant at the 1% level (Table 2). These results indicated that all the training conditions affected the discriminant error. All the first-order interactions were significant at the 5% level except for the following cases; [NN architecture]×[supervisor image] for the fitting error rate, [material]×[image size] and [number of training classes]×[supervisor image] for the CV error rate, [NN architecture]×[image size] and [supervisor image]×[image size] for both discriminant error rates. These results indicated that the combination of training conditions also affected the discriminant error in most of the cases.

In Figs. 3a-f, we show the supervisor images and both

types of discriminant error rates for the respective number of training classes. Table 3 lists the summarized discriminant error rates up to 10 classes for comparison among materials. These error rates were obtained from the SP trained with shape distribution images of 64×64 pixels, because the fitting error rates were the lowest under this combination of training conditions. Hereafter, we will consider only this combination of training conditions.

Regarding the 10 training classes, the fitting error rates in the case of leaf-mustard leaf were the lowest of all materials, followed by maple leaf, soybean leaflet, pear fruit, Tartary buckwheat kernel and mulberry leaf in that order (Table 3). The CV error rates in the case of maple leaf were the lowest, followed by soybean leaflet, Tartary buckwheat kernel, pear fruit, mulberry leaf and leaf-mustard leaf in that order (Table 3). We showed the two contingency tables in the case of maple leaf and soybean leaflet to determine how the CV errors occurred (Figs. 4a-b). In these cases, the discriminant error rates were higher when the shape dissimilarity was low, or when the leaf shape was highly lobed.

The CV error rates were never lower than the fitting

Table 2. Results from analysis of variance

Source	df	Fitting examination			Cross-validation examination		
		Sum of squares	F-ratio	p-value	Sum of squares	F-ratio	p-value
Material (M)	5	0.8064	69.90	0.000	1.4733	280.52	0.000
Number of training classes (C)	2	3.4148	739.99	0.000	6.0833	2895.53	0.000
Neural network architecture (A)	1	0.0305	13.21	0.000	0.0276	26.27	0.000
Supervisor image (S)	1	0.3074	133.23	0.000	0.0103	9.77	0.002
Image size (I)	2	0.0328	7.11	0.001	0.0354	16.86	0.000
M×C	10	0.4124	17.87	0.000	0.6346	60.41	0.000
M×A	5	0.0438	3.79	0.003	0.0301	5.73	0.000
M×S	5	0.1084	9.40	0.000	0.0436	8.30	0.000
M×I	10	0.0823	3.57	0.000	0.0189	1.80	0.064
C×A	2	0.0206	4.46	0.013	0.0159	7.58	0.001
C×S	2	0.1620	35.12	0.000	0.0023	1.12	0.329
C×I	4	0.0251	2.72	0.031	0.0126	3.00	0.020
A×S	1	0.0008	0.33	0.569	0.0048	4.62	0.033
A×I	2	0.0130	2.81	0.063	0.0056	2.67	0.072
S×I	2	0.0027	0.58	0.559	0.0017	0.82	0.442
Error	169	0.3899			0.1775		

We carried out an analysis of variance to determine whether the fitting and cross-validation (CV) error rates varied with the training conditions. In this analysis of variance, we used only 2, 5 and 10 training classes, because the maximum number of classes was 10 in the case of mulberry leaf.

Table 3. Discriminant error rates for 10 training classes

Number of training classes Material	Fitting error rate			Cross-validation error rate		
	2	5	10	2	5	10
Maple leaf	0.000	0.031	0.116	0.000	0.031	0.202
Tartary buckwheat kernel	0.000	0.170	0.230	0.000	0.220	0.380
Pear fruit	0.000	0.115	0.214	0.000	0.138	0.444
Mulberry leaf	0.000	0.232	0.239	0.000	0.326	0.489
Mustard leaf	0.000	0.068	0.084	0.000	0.169	0.513
Soybean leaflet	0.000	0.059	0.118	0.000	0.059	0.225

These discriminant error rates were obtained with simple perceptrons (SPs) trained with shape distribution images of 64×64 pixels.

error rates. In the case of leaf-mustard leaf, the fitting error rates were extremely low, although the corresponding CV error rates were comparatively high (Fig. 3e).

Discussion

We found that a shape distribution image of 32×32 and 64×64 pixels was suitable for learning in the case of many training classes, because learning failure occurred in some training cases with mean shape images of 16×16 pixels. We consider that a sufficiently large image size and continuous pixel intensity of the shape distribution contributed to the linear independence of the supervisor images, because a large grayscale image can describe detail more.

In the fitting examination, the above-mentioned expressiveness of the larger image size and the continuous pixel intensity of the shape distribution seemed to affect the discrimination of the test data. Moreover, we consider that the shape distribution could compensate for intra-class variation with continuous pixel intensity, resulting in a lower fitting error rate than that for the mean shape. In this examination, the HM generally gave higher fitting error rates than the SP, presumably because no stable equilibrium may have been reached during iteration in the case of HM. This problem requires further examination.

In the CV examination, we could not determine why the effects of NN architecture and supervisor images on the CV error rates were not appreciable. This remains to be elucidated. Although no obvious difference was observed in the CV error rates between the HM and the SP, the performance of the SP was superior to that of the HM, because the computational costs for the SP were much lower than those for the HM. Therefore, the SP trained with the 64×64 pixel-images was an optimal combination also in the CV examination.

The discriminant error rates strongly depended on the relation of intra-class variation to dissimilarity between neighboring classes. When intra-class variation exceeded dissimilarity between neighboring classes, some individual shape images could resemble the supervisor image of another training class, resulting in misclassification (Figs. 4a-b).

Difference in the discriminant error rates between the

materials was caused by varying degrees of dissimilarity between neighboring classes and the degree of intra-class variation from one material to another. Namely, the discriminant error rates were comparatively low in the case of maple leaf shape and soybean leaflet shape (Table 3), because these materials exhibited a large dissimilarity between neighboring classes and/or small intra-class variations (Figs. 1a and 1f). The discriminant error rates were comparatively high in the case of the mulberry leaf shape (Table 3), because they exhibited a small dissimilarity between neighboring classes and/or large intra-class variations (Figs. 1c and 1d). Complex shape, as in the case of highly lobed leaf considerably varied within a class (Figs. 1a and 1d), causing a high discriminant error rate (Fig. 4a).

The discriminant error rates rose as the number of training classes increased, because neighboring classes became similar to each other. We selected the training classes so that the sum of the square of the dissimilarity between training classes was maximized. The dissimilarity between classes was defined as the difference between the averages of the first principal components of the standardized elliptic Fourier coefficients of the individual shapes within a class. Therefore, the distribution range of each training class tended to overlap with others, as the number of training classes increased.

We considered that overfitting always occurred, because the fitting error rates were generally higher than the CV error rates under any combination of training conditions. The overfitting to the leaf-mustard leaf shape data was particularly large, presumably because the supervisor images of leaf-mustard leaves were likely to fluctuate depending on which individual leaf was removed as test data in the CV examination.

Chen *et al.* (1989), Liao *et al.* (1993), Rigney and Brusewitz (1993), Ding and Gunasekaran (1994), and Ghazanfari *et al.* (1996) obtained error rates lower than 0.1 in their discrimination of plant shape. The discriminant error rates in this study were comparatively high. However, our discrimination problems were rather difficult to solve because of the relatively large intra-class variations, and since we did not use any shape features in the discrimination, we consider that the results were acceptable. Needless

Number of classes	Supervisor images	Error rate
2		0.000 0.000
5		0.031 0.031
10		0.116 0.202
14		0.147 0.317

(a)

Number of classes	Supervisor images	Error rate
2		0.000 0.000
5		0.170 0.220
10		0.230 0.380
15		0.310 0.557
20		0.400 0.715
25		0.320 0.678
30		0.349 0.738
35		0.351 0.774
40		0.376 0.975

(b)

Number of classes	Supervisor images	Error rate
2		0.000 0.000
5		0.115 0.138
10		0.214 0.444
11		0.213 0.440

(c)

Number of classes	Supervisor images	Error rate
2		0.000 0.000
5		0.232 0.326
10		0.239 0.489

(d)

Number of classes	Supervisor images	Error rate
2		0.000 0.000
5		0.068 0.169
10		0.084 0.513
15		0.090 0.672
20		0.132 0.672
25		0.105 0.715
30		0.108 0.742

(e)

to say, there is room for improvement in the discriminant error rates. For example, inclusion of shape size information and three-dimensional information to our present model is expected to improve the discriminant error rates.

In this study, we showed that NNs with image input could be widely and easily applied even to rather complex shapes such as lobed leaves. We could efficiently carry out the discrimination of any materials by applying our present model, without requiring the extraction of any shape features or modification of the model. Our present model is superior to other methods of plant shape discrimination in this respect. If we used the method based on shape features, we would have to repeat the process of selecting such features for the new materials, and determine whether the method was suitable for these features each time we introduced a new set of materials. Notably, the optimal combination of training conditions (an SP trained with shape distribution images of 64×64 pixels) was common to all the materials examined in this study. These results suggest a wide range of possibilities in applying this combination to new materials without modifying either the NN structure or the supervisor data. Since various shapes of phytoorgans in many species have to be discriminated for genetic resource management, wide applicability of a shape-discriminant

Number of classes	Supervisor images	Error rate
2		0.000 0.000
5		0.059 0.059
10		0.118 0.225
15		0.200 0.393
20		0.154 0.436
25		0.165 0.551
30		0.156 0.611
35		0.139 0.638
38		0.137 0.679

(f)

Fig. 3. Supervisor images and discriminant error rates in all the materials. The supervisor images were sorted in order of the average of the first principal components of the standardized elliptic Fourier coefficients of the individual shapes within a class. The upper and lower numbers show the fitting and cross-validation (CV) error rates, respectively. Both types of discriminant error rates were obtained with simple perceptrons (SPs) trained with shape distribution images of 64×64 pixels. (a) Maple leaf shape, (b) Tartary buckwheat kernel shape, (c) Pear fruit shape, (d) Mulberry leaf shape, (e) Leaf-mustard leaf shape, (f) Soybean leaflet shape.

model would be highly desirable. Our present model would be suitable for such an undertaking.

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		Discrimination by the neural network										Success Failure	
Class of input image		18	2	0	0	0	0	0	0	0	0	18	2
		90%	10%	0%	0%	0%	0%	0%	0%	0%	0%	90%	10%
		0	20	0	0	0	0	0	0	0	0	20	0
		0	100	0	0	0	0	0	0	0	0	100	0
		2	0	15	1	2	0	0	0	0	0	15	5
		10	0	75	5	10	0	0	0	0	0	75	25
		0	0	0	17	0	1	0	0	0	0	17	1
		0	0	0	94	0	6	0	0	0	0	94	6
		0	0	1	0	19	0	0	0	0	0	19	1
		0	0	5	0	95	0	0	0	0	0	95	5
Total		20	26	18	18	22	23	20	19	14	18	158	40
		10	13	9	9	11	12	10	10	7	9	80	20

(a)

		Discrimination by the neural network										Success Failure	
Class of input image		9	1	0	0	0	0	0	0	0	0	9	1
		90%	10%	0%	0%	0%	0%	0%	0%	0%	0%	90%	10%
		0	12	1	0	0	0	0	0	0	0	12	1
		0	92	8	0	0	0	0	0	0	0	92	8
		0	1	7	2	0	0	0	0	0	0	7	3
		0	10	70	20	0	0	0	0	0	0	70	30
		0	0	2	5	0	0	1	0	0	0	5	3
		0	0	25	62	0	0	13	0	0	0	62	38
		0	0	0	1	7	3	0	0	0	0	7	4
		0	0	0	9	64	27	0	0	0	0	64	36
Total		9	14	10	9	8	13	11	10	11	7	79	23
		9	13	10	9	8	12	11	10	11	7	77	23

(b)

Fig. 4. Contingency tables of the cross-validation (CV) error. The cell in the i -th row and the j -th column shows where shapes of the i -th class were discriminated to the j -th class by the neural network. The upper and lower numbers show the absolute and relative frequencies, respectively. The CV errors were obtained with simple perceptrons (SPs) trained with shape distribution images of 64×64 pixels. (a) Maple leaflet shape, (b) Soybean leaflet shape.

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