Japan. J. Breed. 41 : 485～497 (1991)

Quantitative Evaluation of Soybean (*Glycine max* L. MERRILL) Plant Shape by Image Analysis.

Seishi NINOMIYA[1] and Isao SHIGEMORI[2]

[1] *Faculty of Agriculture, University of Tokyo,* Yayoi, Bunkyo-ku, Tokyo 113, Japan
[2] *Nagano Chushin Agricultural Experimental Station,* Shiojiri, Nagano 391-64, Japan

Shape of soybean plants were evaluated by image analysis. Binary soybean images were obtained by thresholding the original video images. Then, two marginal frequency distributions of pixels of plant projection (silhouette) were obtained by scanning each binary image of soybean in both perpendicular (for Y-distribution) and parallel (for X-distribution) directions to the main axis which was defined to be a regression line on the main stem of plants. Because those distributions were obtained after similar transformation of the plant projection that the height became the same among all the plants examined, the range of Y-distributions was fixed while that of X-distributions corresponded to the normalized width of the plants. Therefore, it became possible to compare directly the types of the distributions of different plants. Among 875 plants of 175 varieties, the types of two marginal distributions vary widely and features of the original plant-shape were well represented by those types.

To evaluate the soybean shape quantitatively, 18 variables such as width, height, discrepancy of main axis from the mean of the X-distribution, several central moments of the two marginal distributions, etc. were introduced. Then, those 18 variables were defined to e the shape-indicators of soybean.

The correlation coefficients between each of those shape-indicators and the score on the plant shape given empirically by breeders according to their own judgement were at most about 0.4 in absolute value. And it was concluded that none of them individually could explain the judgement. However, the plants that were judged to be good-shaped by breeders, could be discriminated successfully by the discriminant analysis based on all of those shape-indicators. The efficiency of discrimination was as high as 90%.

KEY WORDS: *Glycine max,* plant shape, plant type, image analysis, discriminant analysis, shape-indicator.

Introduction

Plant shape of soybean (*Glycine max* L. MERRILL) has been one of the important characters on which selection is made in breeding, because it is supposed to reflect to lodging resistance, efficiency of utilization of sun-light, adaptability to machine harvesting, etc. But it sould be emphasized that it has been "supposed" as there have been only a few quantitative measures (for example, height and stem number) about shape of soybean and systematic relation between the shape and those agricultural characters has not been clear yet. In fact, the "good" plant shape of soybean is now selected only empirically by the skillful breeders with few quantitative data.

On the other hand, as the hardware and software for image processing have been becoming substantially powerful, image analyses have been often applied in the field of agricultural biology. It has been also revealed that they can be utilized to evaluate the shape of plants in several stages such as complete plants, leaves, seeds, chromosomes, etc. (FUKUI

Received November 16, 1990.

1990, NINOMIYA 1990, OKA and HINATA 1990). OKA and HINATA (1988, 1989) applied the image analysis to evaluate the shape of rice plants and showed that the shape could be characterized by contour maps of pixel-density in binary images of rice plants. In their study, the complicated shape of rice was clearly summarized in the contour maps. Evaluation of the shape was, however, still qualitative because the visual comparison of the different maps was only the way to compare the differences on the shape.

In this paper, images of soybean plant were analyzed to develop quantitative measures to evaluate the soybean plant shape. Marginal frequency distributions of pixels of plant projection in binary images were obtained instead of the contour maps and several variables from those distributions in addition to ordinary variables such as height, width, etc., were defined to be "shape indicators." Then, it was examined whether those indicators were useful to evaluate the shape of soybean especially in breeding process.

Materials and Methods

Soybean plants were cut at the node of cotyledon at the beginning of the pod growing when the upper-most leaves were fully expanded and the shape of plants were almost fixed at the stage except the case of indeterminate varieties. Then, each plant was naturally placed on a white board (90×180 cm). This procedure was usually simple because three dimensional structure of soybean plants is comparatively "flat" as it will be discussed in **Results and Discussion.** Then, the each plant was video-taped (video camera GXS-11, JVC, Tokyo and video recorder HRS-10, JVC, Tokyo) with a ruler of 1 m long.

The original video image of standard composit signal (NTSC) was devoded into analog red, green and blue (RGB) signals by a decoder (ED-1000N, Photoron Co., Ltd. Tokyo) and the decoded R (red), G (green) and B (blue) signals were digitized into three digital images by a real time A/D converter (Nexus 68320, Kashiwagi Res., Corp., Tokyo). Each of the digital images is composed of 512×480 pixels and each pixel has the memory of 8 bits, so that each pixel is expressed by gray scale of 256 ($=2^8$) steps in each color (256^3 steps in full color image). The digitized images were processed in the color image processor (Nexus 6410, Kashiwagi Res., Corp., Tokyo) which is controlled by a 32-bits personal computer (PC-386, Seiko Epson Co., Ltd. Suwa) through GPIB interface. The images were processed as follows.

(1) The original digitized color image (Fig. 1a) was partially extended around the ruler and the actual length per pixel was estimated by pointing the two ends of an unit length on the ruler with digitizer (Fig. 1b).

(2) Some pixels on a main stem were pointed out by digitizer with human eyes and a line on those points was estimated by linear regression. In this study, the position of a main stem was represented by this line even if it bent. When a main stem was straight, the estimated line was just on the main stem (Fig. 1c). This line will be denoted as main axis, hereafter. In this step, the gray level of images was inverted because the pixels composing a plant were always darker than those of background.

(3) A loose rectangular which roughly surrounded the plant area of an image, was drawn by pointing two pixels on the diagonal positions with digitizer (Fig. 1d) to erase the area of the image outside the plant area which was unnecessary for the analaysis.

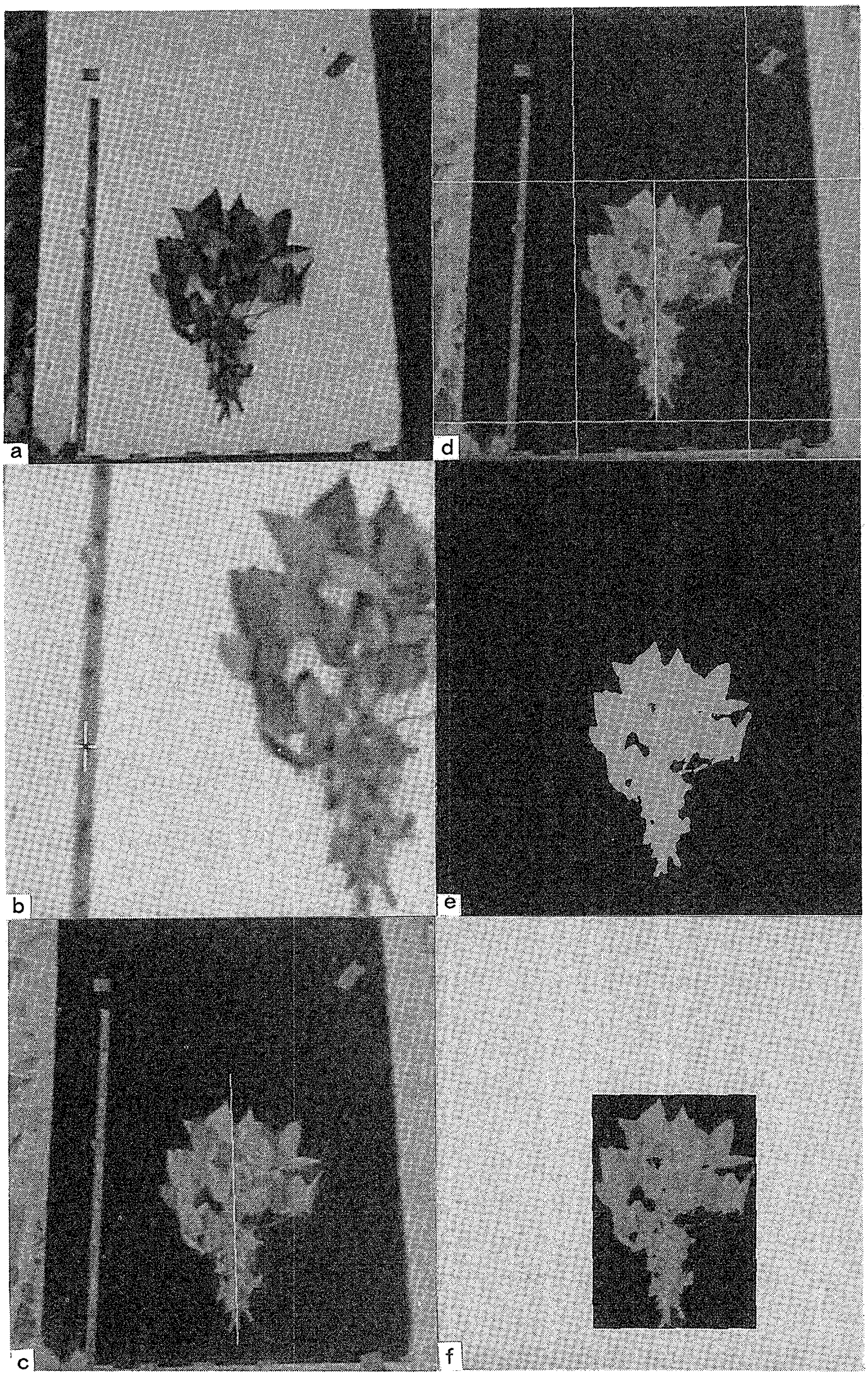


Fig. 1. Operations on the original image. **a**; An original digital image of soybean placed on a white board with a ruler. **b**; Identification of standard points of the ruler on a magnified image with digitizer. **c**; Definition of main axis by linear regression on a main stem. **d**; Setting of a rectangular that roughly surrounds a plant by marking the outer points of a plant with digitizer. **e**; A binary image of soybean obtained by thresholding **f**; Automatic estimation of the width and the height of a plant by finding a rectangular that exactly surronds the plant. see the text for further details.

(4) The binary image of a plant was obtained by thresholding the R digital image (Fig. 1e). The level of the thresholding was decided visually. The level was heuristically stored for the thresholding of the next scene on a video tape. This function was very convenient because the contrast of succeeding scene was usually very similar to the last one and only a little modification on the level was necessary.

(5) An rectangular which exactly surrounded a plant projection was decided automatically where two sides were perpendicular to the main axis and others were parallel to it. The actual length of the former was defined to be width of the plant and that of the latter to be height of the plant (Fig. 1f). The processing time for this automatic procedure was extremely reduced by setting a loose rectangular at the step of (3).

(6) The binary plant image was scanned along the rectangular for both of the directions and the number of the pixels of plant projection in each of the scanning band was counted. Each scan corresponds to a class in frequency distributions. The range of each class was 1/20 of the side length of the rectangular in each direction. Then, two frequency-distributions of 20 classes were obtained. A distribution for the scanning parallel to the main axis is denoted to be a X-distribution (Fig. 2) and the frequency for i-th class is given in number of pixels by $Fx(i)$, $(i=1,2,..., 20$; numbered from the left of the plant) and the comparative frequency by $fx(i)=Fx(i)/\sum_{i=1}^{20}Fx(j)$ where $\sum_{i=1}^{20}fx(j)=1$. A distribution for the scanning perpendicular to the main axis is denoted to be a Y-distribution (Fig. 2) and the frequency for i-th class is given in number of pixels by Fy(i), $(i=1,2,....., 20$; numbered from the top of the plant) and the comparative frequency by $fy(i)=Fy(i)/\sum_{i=1}^{20}fy(j)$ where $\sum_{i=1}^{20}fy(j)=1$.

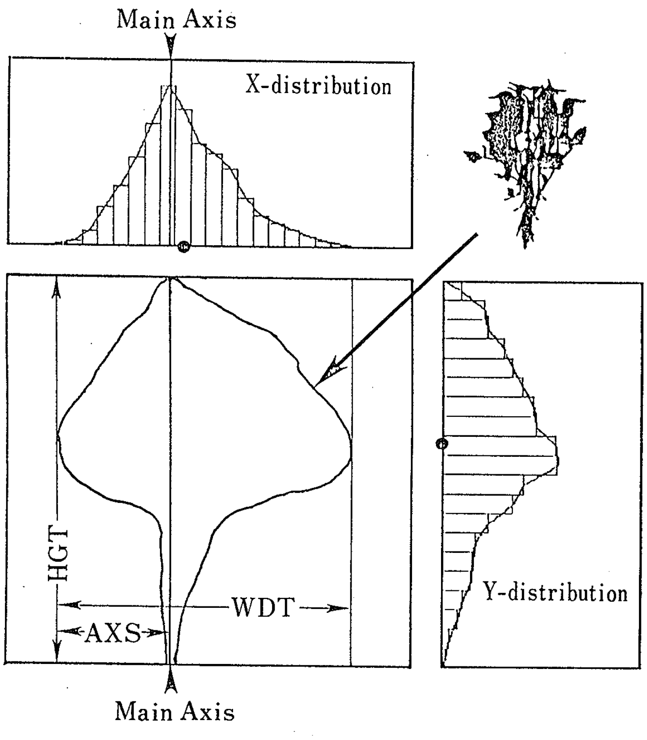


Fig. 2. Schematic design to obtain X- and Y-marginal frequency distributions of binary images of soybean. Main axis was defined to be a regression line on the main stem. Closed circles indicate the means of the distributions. HGT, WDT and AXS indicate the width, the height and the distance between the left end of the plant and the main axis respectively. The graph for X-distribution is always drawn so that the mean of distribution is on the right of the main axis.

The software for the analysis was coded by MASM and N88BASIC on MS-DOS version 3.3.

We examined 875 plants in 176 varieties of soybean in this way (5 plants per variety except some varieties lacking in one or two plants). Those plants were grown at Chushin Agricultural Experimental Station (Nagano Prefecture) in 1987 and were cultivated in the ordinary way at the experimental station.

Results and Discussion

Types of X- and Y-distributions varied widely among 875 plants examined and the types of the distributions themselves seemed to represent the soybean plant shape. In Fig. 3, typical examples of binary images of soybean plants and their X- and Y-distributions are shown. In the figure, each set of X- and Y-distributions shows the average within a variety and each binary image is a representative of each variety. Because those distributions are shown after the similar transformation of plant projections that the height becomes the same among all the plants, then the range of Y-distributions is the same among all the plants while the range of X-distributions corresponds to the comparative width of the plants under the assumption of the same height.

Here, we denote the varieties as **a, b, c, d, e, f, g, h, i** and **j** (Fig. 3). **a** and **b** resembled each other in the narrow range of X-distributions and the trapezoidal type in Y-distributions. Their shape was thin and leaves distribute roughly equal at the upper two-thirds of plants. However, they were distinguishable in D (Table 2. see succeeding text for the definition of D). In fact, the leaves had grown thicker in **b.** Variety **c** also showed a trapezoidal Y-distribution. The range of the X-distribution (this corresponds to WDT* defined later) was, however, larger and D was very low. Varieties **d** and **e** were similar in the broad range of X-distributions and symmetrical Y-distributions. It is the reflection of the round shape of them, although they were distinguishable in D again. Variety **f** showed the heavy-head type of a Y-distribution and the mean of the distribution located in the upper part of the plant, consequently. Variety **g** was the case of less heavy-head type of Y-distribution. The type of Y-distribution in **h, i** or **j** was not distinctive and similar to one of above examples **(a-g)**. The type of X-distributions was, however, trapezoidal or round and was different from the triangular type in the above examples. And the discrepancy between the main axis and the mean of the X-distribution which corresponds to XD1 as defined later, was comparatively large in **h, i** and **j.** Especially the main axis of **j** located nearly the tail end of the distribution. Usually this was caused by lodging or bending and the discrepancy was considered to be used as the indicator of the degree of lodging or bending.

The shape of plants could be somehow explained in the way of preceding arguments about the type of distributions, although the explanation was still qualitative. Then, we defined the following variables obtained from image data to evaluate the shape quantitatively. The width of the plant was defined previously and denoted to be

$$\text{WDT (mm)} \qquad (1)$$

as shown in Fig. 2. The height of the plant was also defined previously and denoted to be

$$\text{HGT (mm)} \qquad (2)$$

as shown in Fig. 2. The area of a plant projection is given by

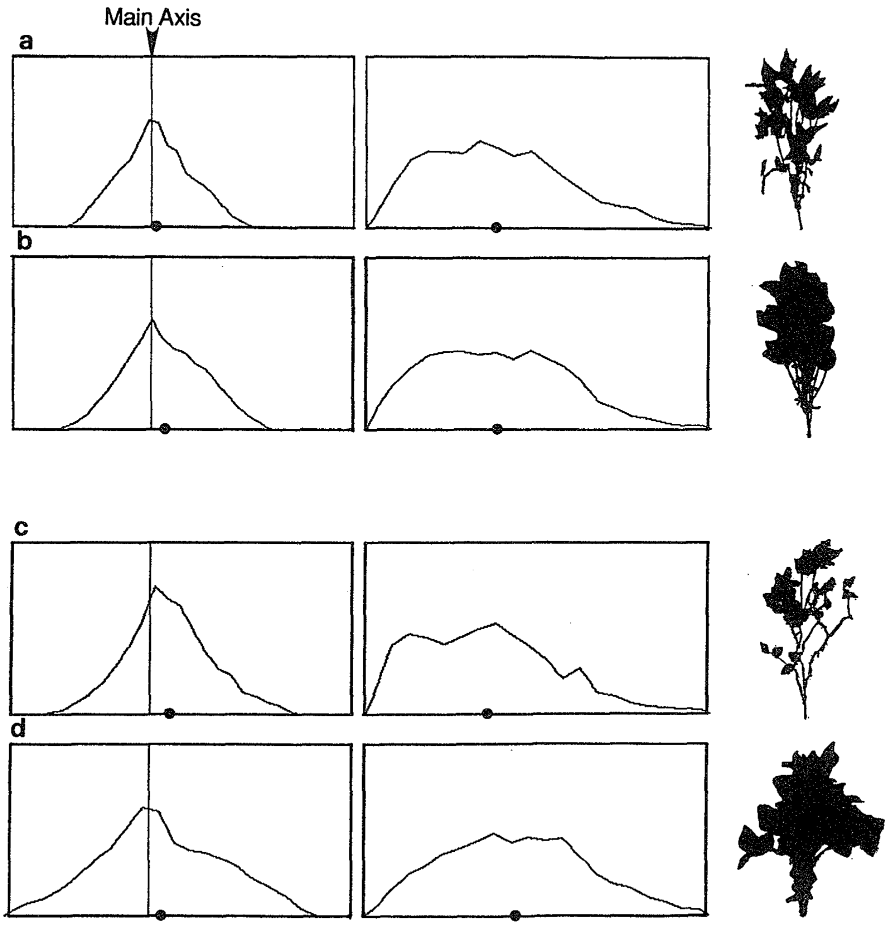
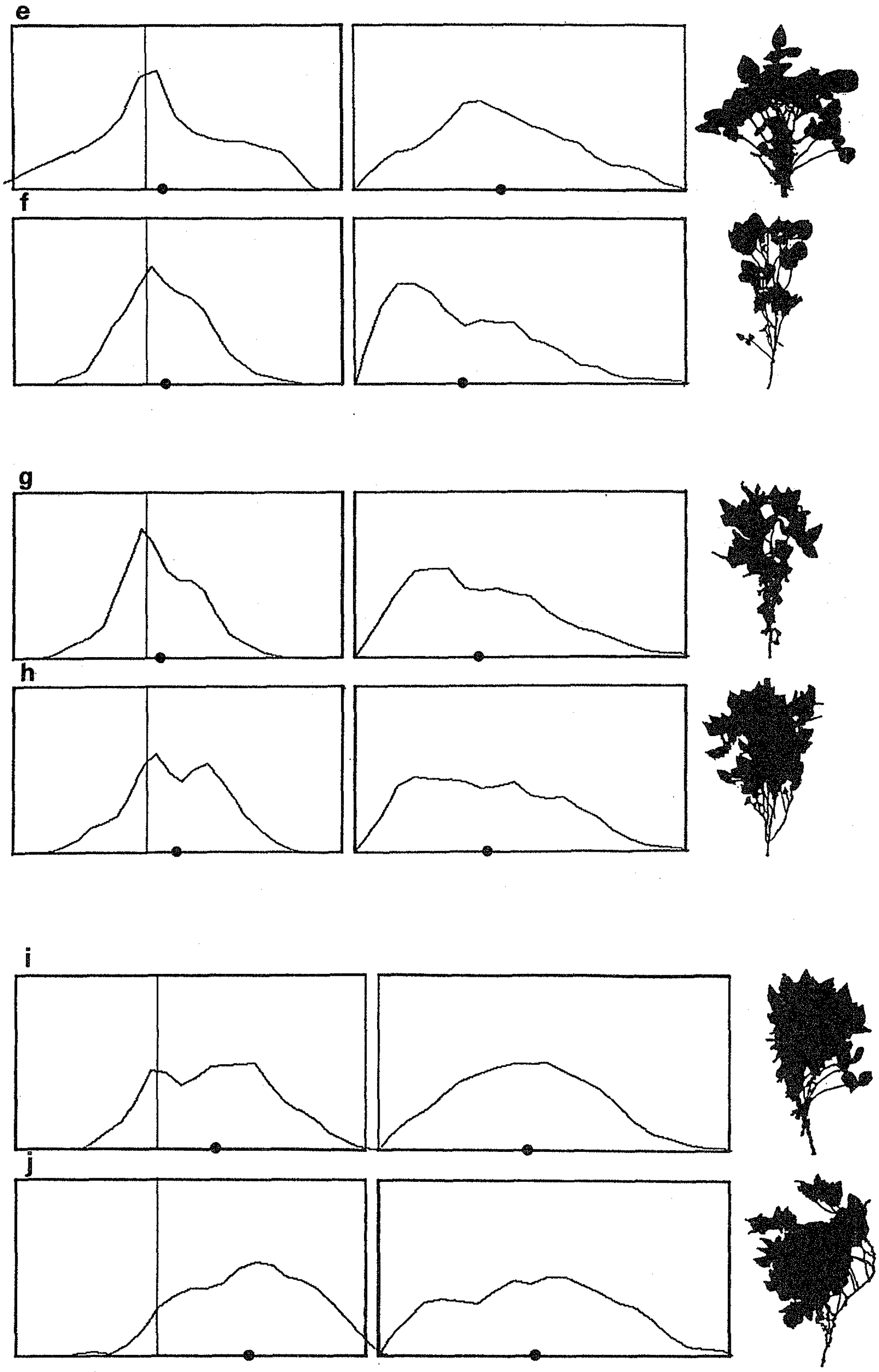


Fig. 3. Typical examples of X and Y-marginal frequency distributions of binary images of soybean. Each set (**a** to **j**) shows the mean frequency of a variety. The distributions on the left are X-distributions and those on the right are Y-distributions. The right-end of Y-distribution corresponds to the base of the stem. The vertical bar in the X-distributions indicates the main axis (the regression line on the main stem) and closed circles indicate the means of those distributions. The binary image (plant projection shown beside each set of the distributions is represented by a single plant of each variety (because it is not possible to obtain a mean binary image of binary images). Notice that, because the distributions are shown after the similar transformation, the range of X-distributions comparatively corresponds to WDT* (normalized width) while the range of Y-distributions is the same. The distance between the closed circle and the vertical bar in X-distribution corresponds to XD1. See the text for further details. **a**; Tachinagaha, **b**; Tamamusume, **c**; Miyagishirome, **d**; Tsurukogane, **e**; Prize, **f**; Asomasari, **g**; Kitamusume, **h**; Chiyohime, **i**; Waseasahi, **j**; Fukuyutaka.

$$\mathrm{AREA} = p^2 \sum_{i=1}^{N} Fx(i) \text{ or } \mathrm{AREA} = p^2 \sum_{i=1}^{N} Fy(i) \ (\mathrm{mm}^2), \tag{3}$$

where p and N are the actual length per pixel and the number of classes of the frequency distributions, which is fixed to 20 in this study, respectively. The degree of occupancy of a plant projection in the rectangular is defined to be



(Fig. 3 continued)

$$D = AREA/(WDT \cdot HGT) \qquad (4)$$

and this can be an indicator of the thickness of plant growth.

The following indicators are given in normalized values after the similar transformation on the shape of plants that the height of them becomes common among all the plants examined. Therefore, the shape of different plants can be directly compared with those indicators. The normalized width after the similar transformation that the height of all the plants is fixed to be 1000 mm, is defined to be

$$\mathrm{WDT}^* = 1000\ (\mathrm{WDT}/\mathrm{HGT})\ (\mathrm{mm}) \qquad (5)$$

The mean of a X-distribution is given by $\mathrm{XM} = \sum_{i=1}^{N} \mathrm{WDT}^*(i\text{-}1/2) fx(i)/\mathrm{N}$ (mm) and that of Y-distribution is by

$$\mathrm{YM} = \sum_{i=1}^{N} 1000(i\text{-}1/2) fy(i)/N\ (\mathrm{mm}), \qquad (6)$$

where N is the number of classes of the frequency distributions. Then, the discrepancy between the mean of a X-distribution and the main axis is defined to be

$$\mathrm{XD1} = |1000 \cdot \mathrm{AXS}/\mathrm{HGT}\text{-}\mathrm{XM}|\ (\mathrm{mm}), \qquad (7)$$

where AXS is the distance between the left end of a plant and the main axis (value before the similar transformation; Fig. 2) and this can be an indicator of bending of plants. And the discrepancy between the mid range of a X-distribution and the main axis is defined to be

$$\mathrm{XD2} = |1000 \cdot \mathrm{AXS}/\mathrm{HGT}\text{-}\mathrm{WDT}^*/2|\ (\mathrm{mm}). \qquad (8)$$

The standard deviations for X- and Y-distributions are given by

$$\mathrm{XSD} = \sqrt{\sum_{i=1}^{N} (\mathrm{WDT}^*(i\text{-}1/2)/\mathrm{N}\text{-}\mathrm{XM})^2 fx(i)} \qquad (9)$$

and

$$\mathrm{YSD} = \sqrt{\sum_{i=1}^{N} (1000(i\text{-}1/2)/\mathrm{N}\text{-}\mathrm{YM})^2 fy(i)}. \qquad (10)$$

The coefficients of variation are given by

$$\mathrm{XCV} = \mathrm{XSD}/\mathrm{XM} \qquad (11)$$

and

$$\mathrm{YCV} = \mathrm{YSD}/\mathrm{YM}. \qquad (12)$$

The skewness for both of the distributions are given by

$$\mathrm{XSK} = \sum_{i=1}^{N} (\mathrm{WDT}^*(i\text{-}1/2)/\mathrm{N}\text{-}\mathrm{XM})^3 fx(i)/\mathrm{XSD}^3 \qquad (13)$$

and

$$\mathrm{YSK} = \sum_{i=1}^{N}(1000(i\text{-}1/2)/\mathrm{N}\text{-}\mathrm{YM})^3 fy(i)/\mathrm{YSD}^3. \quad (14)$$

The kurtosis for both of the distributions are given by

$$\mathrm{XKU} = \sum_{i=1}^{N}(\mathrm{WDT}^*(i\text{-}1/2)/\mathrm{N}\text{-}\mathrm{XM})^4 fx(i)/\mathrm{XSD}^4 \quad (15)$$

and

$$\mathrm{YKU} = \sum_{i=1}^{N}(1000(i\text{-}1/2)/\mathrm{N}\text{-}\mathrm{XM})^4 fy(i)/\mathrm{YSD}^4. \quad (16)$$

The discrepancy of X- and Y-distributions from uniform distributions are defined to be

$$\mathrm{XFT} = \sum_{i=1}^{N}|fx(i)\text{-}1/\mathrm{N}| \quad (17)$$

and

$$\mathrm{YFT} = \sum_{i=1}^{N}|fy(i)\text{-}1/\mathrm{N}|. \quad (18)$$

Those 18 variables, (1)–(18) were defined to evaluate the soybean shape and they will be denoted to be shape-indicators. Some statistical estimates of the indicators are shown in Table

Table 1. Mean, standard deviation, minimum and maximum values for the varietal mean of the shape-indicators (S.I.) estimated from image data

S.I.	Mean	s.d.	Minimum	Maximum
WDT	515.1	74.7	326.2	710.5
HGT	855.8	110.7	473.9	1095.4
D	0.3220	0.0428	0.2212	0.4496
AREA	142373	34242	61518	250884
WDT*	609.56	92.89	369.94	925.07
XD1	98.20	60.97	11.46	275.58
XD2	22.37	8.95	5.12	70.77
YM	389.8	29.8	306.8	460.0
XSD	129.3	22.1	75.5	199.1
YSD	200.4	10.4	174.1	228.5
XCV	0.4239	0.0284	0.3539	0.5108
YCV	0.5192	0.0361	0.4488	0.6235
XSK	0.2008	0.0837	0.0390	0.4745
YSK	0.3883	0.1811	−0.0209	0.9459
XKU	2.349	0.195	1.901	3.056
YKU	2.680	0.324	2.178	4.006
XFT	0.01878	0.00417	0.01219	0.04326
YFT	0.02485	0.00489	0.01451	0.04020

1, where the estimations were based on the vrietal means. The minimum and maximum values show the wide range of variation in the indicators and the results of the analysis of variance showed the significant varietal difference ($p<0.01$ for all the shape-indicators). The mean values of the shape-indicators for the varieties adopted as examples in Fig. 3 are shown in Table 2.

Apart from the above investigation, we asked some soybean breeders to watch the same video images as used for the image analyses and to give a score (1, 2 or 3; 1 for "bad", 2 for "medium" and 3 for "good") to each plant according to their empirical judgements on the plant shape. Then, the relation between the shape-indicators and the scores given by the breeders was examined as follows.

First, the correlation coefficients between the shape-indicators and the score were estimated (Table 3). They are about 0.4 at the maximum in absolute value. Although even the correlation coefficients as low as 0.1 are significant at 1% level because of high degree of freedom (d.f. = 873), the values were too low to assume the linear relation between the score and any shape-indicator. That is, no single shape-indicator alone was found to be substituted for the human judgement on the shape.

Second, a discriminant analysis based on all of the 18 indicators, was made to develop a multidimensional discriminant function about the score. For the purpose, the DISCRIM procedure in SAS (SAS INSTITUTE INC. 1985) based on the generalized squared distance (RAO 1973) was used. The results are shown in Table 4. The net rate of correct discrimination about the scores, where the discrimination by the discriminant analysis and by the breeders was agreed, was only 68.6%

Table 2. The mean values of the shape-indicators for the varieties shown in Fig. 3. **a**, **b**, ..., **j** correspond to those in Fig. 3. Notice that YM is measured from the top of plant (from the left-end of Y-distribution in Fig. 3)

	WDT	HGT	D	AREA	WDT*	XD1	XD2	YM	XSD	YSD	XCV	YCV	XSK	YSK	XKU	YKU	XFT	YFT
a Tachinagaha	465.8	979.6	0.3365	153704	477.6	12.84	11.63	377.5	98.43	198.1	0.4259	0.5257	0.1449	0.4165	2.460	2.586	0.01854	0.023
b Tamamusume	445.5	862.2	0.3890	149367	520.3	39.49	21.12	380.8	109.99	198.6	0.4322	0.5218	0.2133	0.3332	2.417	2.604	0.01643	0.023
c Miyagishirome	506.8	959.0	0.2500	118615	534.5	57.03	30.23	352.0	107.09	197.7	0.3929	0.5624	0.2703	0.5056	2.544	2.858	0.02165	0.027
d Tsurukogane	418.1	532.8	0.3910	86333	785.7	37.68	10.76	439.7	173.21	202.8	0.4483	0.4618	0.0961	0.2041	2.308	2.545	0.01515	0.020
e Prize	620.8	672.2	0.3181	132771	925.1	49.76	31.02	438.4	199.12	203.1	0.4043	0.4650	0.2084	0.2577	2.545	2.547	0.02185	0.021
f Asomasari	551.2	993.3	0.3257	182683	553.0	55.65	25.88	319.3	118.00	197.7	0.4331	0.6235	0.2475	0.6787	2.435	2.855	0.01629	0.031
g Kitamusume	385.9	666.9	0.3469	88442	577.9	38.62	19.54	370.7	116.75	200.2	0.3807	0.5416	0.1818	0.5263	2.354	2.655	0.02040	0.025
h Chiyohime	524.0	973.9	0.3748	193691	537.8	91.37	21.20	396.0	110.57	206.0	0.3913	0.5200	0.2154	0.2713	2.396	2.262	0.01863	0.020
i Waseasahi	503.8	748.6	0.3940	145254	674.1	168.29	31.20	419.4	151.65	187.3	0.4626	0.4488	0.1449	0.1626	2.152	2.618	0.01340	0.024
j Fukuyutaka	710.5	939.6	0.3628	239319	755.0	261.73	25.28	440.8	165.94	210.3	0.4574	0.4788	0.1762	−0.0209	2.231	2.190	0.01351	0.018

Table 3. Correlation coefficients between the shape-indicators and the scores given empirically by breeders according to the shape of soybean plants. The probability that the coefficient is larger than the value, is shown in the parentheses (d.f. = 873)

WDT	HGT	D	AREA	WDT*	XD1
−0.17815	0.02172	0.40820	0.12401	−0.19224	−0.41266
(0.0001)	(0.5211)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
XD2	YM	XSD	YSD	XCV	YCV
−0.14038	0.06692	−0.23853	−0.15973	−0.13882	−0.07389
(0.0001)	(0.0478)	(0.0001)	(0.0001)	(0.0001)	(0.0288)
XSK	YSK	XKU	YKU	XFT	YFT
−0.17846	0.10228	0.03154	0.04883	−0.02061	−0.06790
(0.0001)	(0.0025)	(0.3515)	(0.1490)	(0.5426)	(0.0447)

Table 4. Results of discriminant analysis (SAS procedure; DISCRIM) for the scores on plant shape. The analysis was based on all of the shape-indicators defined in this study. The upper number in each cell indicates the number of plants and the number in each parentheses is the proportion in %. Within-groupe covariance matrices were used for the calculation. The average values of the scores given to each plant by some breeders were rounded to integer and used for the the calculation

		Scores given by DISCRIM			
		1	2	3	Total
	1	181	76	23	280
		(64.64)	(2.714)	(8.21)	(100.00)
Scores given	2	53	247	104	404
by breeders		(13.12)	(61.14)	(25.74)	(100.00)
	3	5	14	172	191
		(2.62)	(7.33)	(90.05)	(100.00)
	Total	239	337	299	875

($=100\times(181+247+172)/875$). However, the rate of the correct discrimination only for the score of 3 was over 90.1%. This fact is extremely important when we consider to apply this procedure to the selection in soybean breeding, because it is much more significant to select (or not to leave) "good ones" than to discard "bad ones". It means that 90.1% of decision by human eyes to select "good-shaped" soybean can be substituted by the discriminant analysis based on the shape-indicators. The reduction of the dimension was tried by excluding some of the 18 shape-indicators, but no combination of less variates resulted better discrimination than the original combination of the 18 variates. Although the functional relation between the human judgements and the shape-indicators is still unknown, the results of the discriminant analysis strongly suggest that those indicators are highly useful to

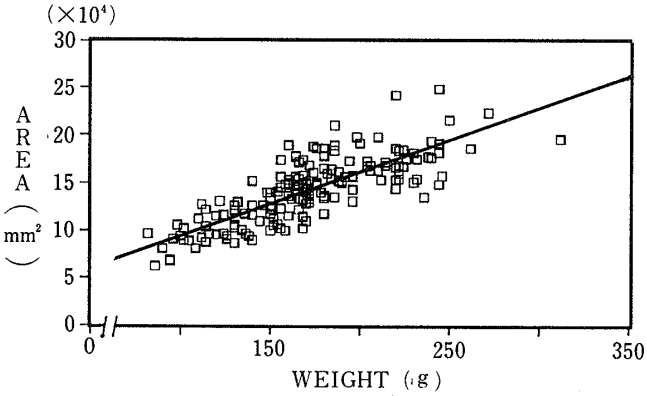


Fig. 4. The relationship between weight and AREA. Each open square represents the mean of a variety. The correlation coefficient is 0.79 (d.f. = 174). y = 660x + 29464.

describe the shape of soybean and to emulate the decision of human eyes, especially in selection.

Information about weight is difficult to obtain from image data. However, Fig. 4 shows the linear relation between weight and area (AREA) of 2-D projection of soybean plants. This relation indicates that the 3-D shape of soybean plant is somehow "flat" and it agrees with our empirical observation on the shape of soybean grown in fields. In other words, 2-D projection of a soybean plant contains even the information about the 3-D shape of soybean and, for example, YM and XM may be used to estimate the centroids of plants which are now estimable only by the stratified clipping method. The similar linear relation between weight and area of binary image was also reported in wheat (SYMONS 1988).

In this study, we did not consider leaf-shape, leaf-angle, petiole-length, or stem-shape, etc. that are also components of physical shape of soybean. After including those components in the analysis, it is supposed that the quantitative evaluation of soybeam plant shape will be more precise and that not only the emulation of human eyes but the direct analysis of the relation between physical structure of plants and agricultural characters such as efficiency of light perception, etc. will be realized.

Acknowledgement

We would like to express our special thanks to all the members of the soybean breeding section of the Chushin Agricultural Experimental Station for their kind help especially for sampling data and cultivating soybean for this study. This study was partly supported by Grant-in-Aid from the Ministry of Education, Science, and Culture of Japan.

Literature Cited

FUKUI, K 1990. Utilization of image data for breeding. 1. Image analysis methods in the chromosome research, present and future. In "Ikushugaku Saikinno Sinpo 31", Japanese Society of Breeding (ed.), Yokendo Publisher Ltd., Tokyo, 125–134, (in Japanese).

NINOMIYA, S 1990. Utilization of image data for breeding. 3. Analysis of binary image and its application. In "Ikushugaku Saikinno Sinpo 31", Japanese Society of Breeding (ed.), Yokendo Publisher Ltd., Tokyo 143–152, (in Japanese).

OKA, M and K. HINATA 1988. An application of computer image analysis for characterization of plant type in rice cultivars. Japan. J. Breed. **38** : 449–458.

——— and ——— 1989. Comparison of plant type between new and old rice cultivars using computer image analysis. Japan J. Crop Sci. **58** : 232–239.

——— and ——— 1990. Utilization of image data for breeding. 2. Evaluation of structure and physiological state of single plant and canopy by image analysis. In "Ikushugaku Saikinno Sinpo 31", Japanese Society of Breeding (ed.), Yokendo Publisher Ltd., Tokyo, 135–142, (in Japanese).

RAO, C. R. 1973. "Linear Statistical Inference and Its Applications", 2nd ed., John Willey & Sons, New

York, p625.

SAS INSTITUTE INC. 1985. "SAS Users' Guide: Statistics Version 5 Edition". SAS Institute Inc. Cary, p986

SYMONS, S. J. and R. G. FULCHER. 1988 Determination of wheat kernel morphological variation by digital image analysis: 1. Variation in eastern canadian milling quality wheats. J. Cereal Sci. **8**: 211–218.

画像解析によるダイズ草姿の定量的評価

二宮正士[1)]・重盛　勲[2)]

([1)]東京大学農学部，東京都文京区，〒113
[2)]長野県中信農業試験場，塩尻市，〒391-64)

ダイズ草姿は受光態勢，耐倒伏性等に反映しひいては収量に関係する形質として育種上選抜の対象となっている．しかし，草姿の評価は多分に定性的で，育種家の経験的な判断によっているのが現状である．そこで本研究は近年発展の著しい画像解析技術を利用してダイズ草姿を定量的に評価する方法を考案しその育種への応用性を検討することを目的としている．

開花後ほぼ草姿が固定した時期に，ダイズ植物体を子葉節で切断し，白板の上に1個体ずつ配置してビデオで録画した．ビデオ画像をデジタル化後ダイズ草姿部分のみを抽出した二値画像を得た (Fig. 1)．その画像を主茎上の数点の直線近似で求めた直線（主軸）に平行でかつ各辺が二値画像とちょうど接するような長方形で囲み (Fig. 1)，各辺の長さで植物体の高さと幅を定義した．さらにその長方形を垂直・平行の2方向に走査し，二値画像で植物体の占める画素数についてふたつの周辺頻度分布を求め，垂直走査に対し X 分布，平行走査に対し Y 分布とした (Fig. 2)．以上の操作でダイズ 176 品種 875 個体を解析した．その結果，植物体の全高が調べた全植物体で等しくなるように相似変換して大きさの要因を取り除き X，Y 分布を表わすとその分布形が草姿の特徴をうまく表現していることが示された (Fig. 3)．さらに植物体の実幅，実高，相似変換で標準化された植物体の幅，植物体の倒伏などによる歪みの指標と考えらる主軸位置と X 分布の平均位置の間の絶対偏差などに加え，各分布の平均，標準偏差，歪度，尖度，一様度（一様分布からの絶対偏差の和）など合計 18 個のパラメータを草姿の形状指数と定義した (Table 1)．ダイズ育種家による経験的な判断に応じて与えられたスコアとそれら形状指数間の相関係数は全般に低く (Table 3)，ひとつの形状指数単独ではそのスコアを説明できなかった．しかしそれら全てを同時に用いた判別分析ではとくに「形状良好」と育種家に判定された個体のうち 90% 以上が同様に判別され (Table 4)，今後いくつかの改良を重ねることで選抜の補助手段として利用可能なことが示された．