Morphometrics for Shape Analysis in Kansei Engineering

Shigekazu Ishihara † and Keiko Ishihara ††

† Dept. of Kansei Design, College of Psychological Science,
Hiroshima International University
†† Dept. of Communication, College of Psychological Science, HIU
†,†† 555-36, Kurose-Gakuendai, Higashi-Hiroshima, 739-2695 JAPAN
†Tel: +81-823-70-4890, Fax:+81-823-70-4852
††Tel: +81-823-70-4877, Fax:+81-823-70-4852
E-mail: i-shige@he.hirokoku-u.ac.jp

Keywords: Kansei analysis, Morphometrics, Shape analysis, Statistics, Geometry, Multivariate analysis

1. Introduction

In Kansei engineering, we have been treated sample shapes as categorical variables (nominal scale). Typical coding are such like long tall / short / cubic or round / square corners. Categorically coded design elements are assigned as *X*s, Kansei evaluation value on a Kansei word is assigned as *Y*, then weights on *X*s are solved with Quantification Theory Type I. This way of analysis is useful in the practical applications those have compounds of various types of design elements. Meanwhile, the shapes had not been treated as mathematical quantity for long time of Kansei studies.

In this study, we use methodologies of Morphometrics to deal with shapes, which have been developed in paleontology. It converts shapes into statistically treatable values, and then we seek the relations with Kansei. By dealing with shapes as values, we can analyze shapes from the basic statistics such as distribution type, to model building with multivariate analyses like classification or projection onto lower dimensional space. Then, we can build mathematical models of shape space and relations between shapes and Kansei. Kansei can be realized as detailed shape of concrete product.

Morphometrics has been developed in paleontology field to statistically analyze shapes of fossilized ancient beings. When comparing fossil shape variations by different places, we cannot find exact same age samples, thus their sizes differ. Also, fossils don't have standard horizontal or vertical basis line or plane, then we have to align them with rotation to minimize the direction differences.

In this study, we analyzed car headlights, and the situation is quite similar. Head light size varies with cars, and many cars have oblique shaped lights. From the front view, their directions are also different. Some lights have upward shape, and others are horizontal shape.

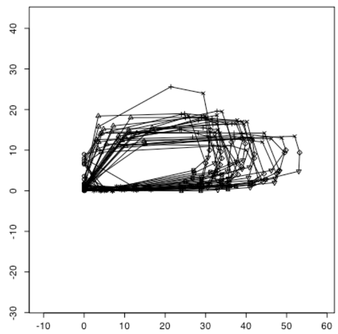

Figure 1. Raw data plots of measured headlights.

Figure 1 shows the raw data of measured left headlights shape. Twenty-seven lights shapes are drawn by setting left lower corner as an anchoring point. It shows the two problems. One is the choosing of anchoring point. If we choose one landmark as an anchoring point, its distribution is very small and the distributions other distant points become larger. In the figure, left end landmarks' distributions are quite large. Distribution of each landmark is quite different, thus, multivariate analysis can not be applied. The second problem is orientation and size. Some samples are oblique and some are smaller or larger. Standardization of both orientation and size are required.

2. Methodologies of Morphometrics

Morphometrics has been developed mainly in paleontology to analyzing shapes of fossils statistically. Shapes are expressed as coordinates of morphological and / or functional landmarks. The *m* landmarks on 2 dimensional plane are represented in 2 by *m* dimensional data. As we noted before, sizes have to be standardized.

Size standardization uses the idea of centroid size (Bookstein, 1991). At first, centroid of each shape is computed and assigned it to the center 0. Centroid size is the sum of the squared distance from the centroid to each landmark. Size standardization is done with equalize centroid sizes between samples.

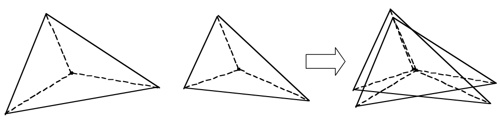

Figure 2. Standardization with centroid size

For orientation alignment by rotation, we used "Generalized Procrustes (GP) method" (Dryden & Mardia, 1998). GP minimized the squared distances between corresponding landmarks between samples. With centroid size and GP method, we can treat the landmark coordinates as multidimensional normal-distributed values.

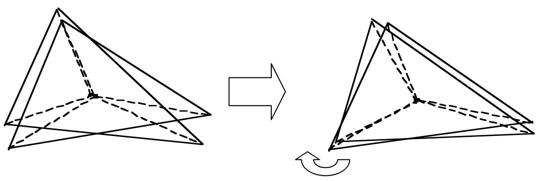

Figure 3. Orientation alignment with Generalized Procrustes method

Since assurances of normal distribution of GP treated landmarks were provided in works published in 1994 to 1998, statistical analysis of landmarks became reality in very recently.

3. Shape Measurement and Morphometrics Treatments

We conducted Kansei evaluation experiment on 27 passenger car headlights. Before the analysis, headlight shapes are measured from 27 Japanese and imported sedans and mini-vans. The headlight photo is taken from 1m distance of left headlight with the digital camera.

From the photos, light shape's coordinates were measured by superimposing mesh photo. Morphological landmarks (maximum curvature points) and functional landmarks (boundary between direction indicator part) are marked. Eight landmarks were taken; (from the front face) leftmost end, max curvature points to the left end (upper and lower), boundary between direction indicator (upper and lower), max curvature points of the direction indicator (upper and lower) and right end.

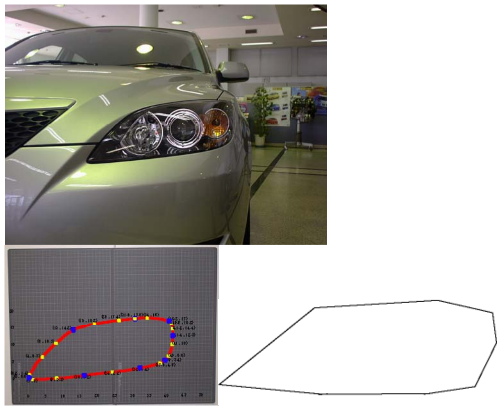

Figure 4. Measurement of headlight and the shape of 8 landmarks (Mazda Axela)

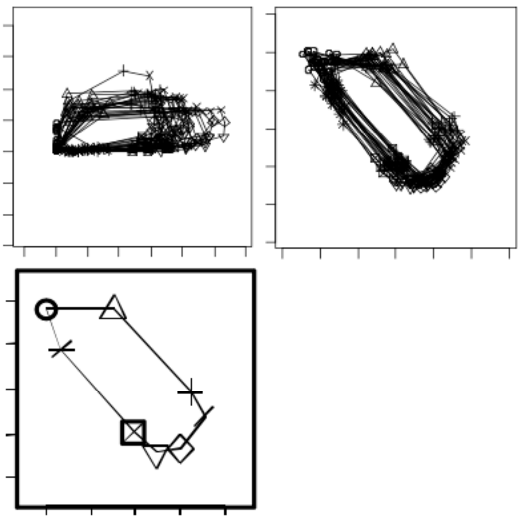

Figure 5. Left to right; Raw data shape of 27 lights, Standardized shape with GPA , Bottom: A light shape after GPA

Twenty-seven measured landmark shapes were computed size standardization and generalized procrustes analysis. For GPA computation, we used “Shapes” package written by Dryden & Mardia (1998), which runs on R statistical analysis environment. Shapes package can be downloaded from CRAN, the repository of R project.

4.Kansei evaluation experiment

Twenty-eight GPA treated shapes (27 and the mean shape) were used as evaluation stimuli. Evaluation stimuli were the shapes of lined 8 landmarks. We used common drawing of bumper and bonnet (hood) between the stimuli, to avoid influence of car differences.

The questionnaire with 58 Kansei words on 5-point SD scale was used. Subjects were unpaid 13 males (12 of 20-23 years old and one 41 years old).

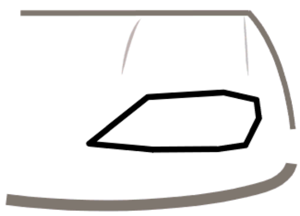

Figure 6. Evaluation stimulus

5.Cluster analysis of shape

At first, shape cluster analysis (Euclid distance, UPGMA) on 28 lights (27 sample + a mean shape) those have 16 dimension data (8 landmarks by 2 dimensions) was performed. We decided 8 cluster solution is appropriate due to the distance change.

Mean Kansei evaluation value of each cluster was computed. The Kansei words those have rated higher than 3.52 (mean evaluation value + 1SD) were regarded as features on the cluster.

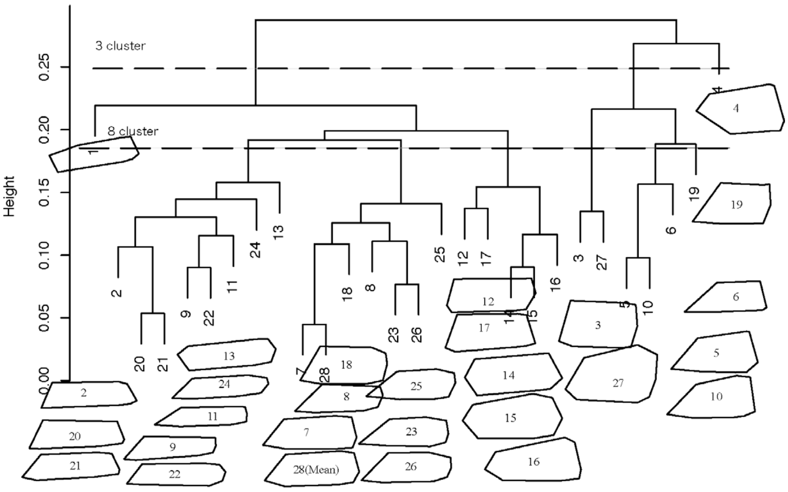

Figure 7. Shape cluster analysis result

On cluster #2 (left, sample 2, 20, 21,.. 13), “slim”, “simple”, “adult” and “sporty” have higher value. Samples belong to cluster #2 have lower height and cusp tails. Cluster #3 (7, 28, … 25) which includes the mean shape (28) has no higher evaluated words. Samples belonging to cluster #3 have middle height and narrow cusp. Samples belong to cluster 4 (12, 17, … 16) have hexagonal shape and have higher value on “masculine”. Cluster #6 (right, 5,10, 6) samples were wedge shaped and higher on “futuristic”, “young”, “casual” and “bright”. Major shape variation and Kansei were identified by this cluster analysis on shape.

6. Principal Component Analysis of Shape

Next, we have done principal component analysis of shapes. Doing principal component analysis of shapes is the projection of shapes those have higher dimensional space onto the smaller dimensional space. In this study, headlights are expressed in 8 (landmarks) by 2 (dimension) data, thus their shapes distributed on 16 dimensional space. Sixteen dimensions are hard to understand, then PCA is the useful tool to considering the shape variation and tendencies

Three major principal components were identified with PCA. Three principal components (PCs) explain 77.9% of total variations. Figure 8 shows the principal component scores of shapes on 3 principal components.

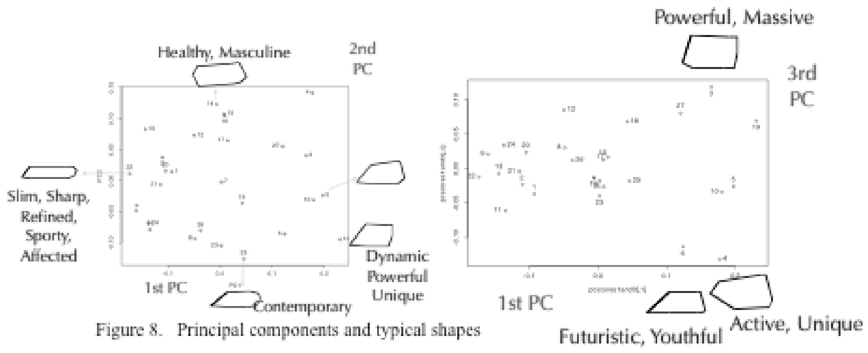

Figure 8. Principal components and typical shapes

In the next figure, we plot the coordinates of landmarks those correspond to –3SD, mean and +3SD theoretical values along the each PC. Upper row is the 1st PC, middle is the 2nd and lower row is the 3rd PC. By the optimization computation of rotation alignment, the shapes are rotated -51 degree. Deformation grids by Thin Plate Spline (TPS) method (Bookstein, 1991) are shown in the rightmost column. These grids show changes of shapes along the mean shape to +3SD .

The 1st principal component shows the variation of thickness, and it roughly corresponds to affine transformation (linear global deformation). Thicker samples have higher value on "unique", "powerful" and "massive". Thinner samples have high value on "slim", "sporty" and "simple". The 2nd PC shows the difference (cusp or no cusp) on inner tail of an eye and it corresponds to non-affine transformation (local deformation). On minus direction (cusp), "slim" and "sharp" are high. On plus direction (no cusp), "young" and "sporty" are high. The 3rd PC shows the mutation from wedge to box shape and also corresponds to local deformation. There are change on curvature of left tail and movement of maximum curvature point of right tail. Wedge has high on "futuristic", "urbanized", boxy has high on "powerful" and "massive". With shape principal component analysis, we decompose variations of light design into major design components; thickness, tail cusp and wedge-boxy.

References

Dryden, I.L. & Mardia, K.V., (1998), *Statistical Shape Analysis*, Wiley, Chichester, UK.

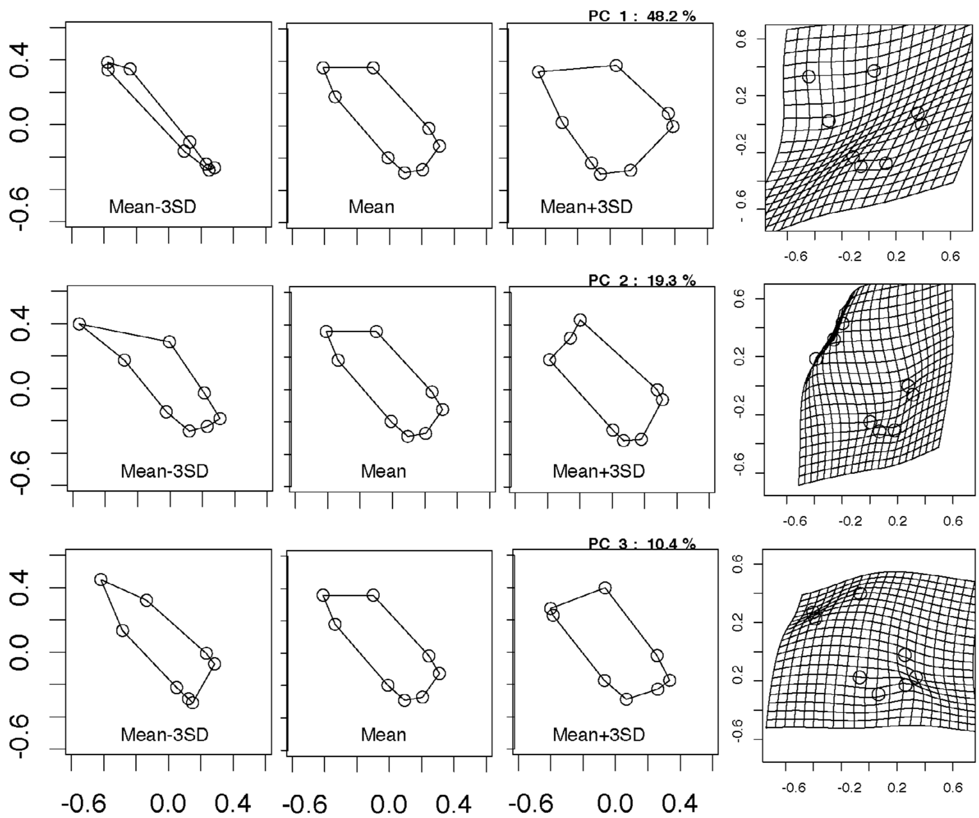

Figure 9. Shape variation along 3 PCs. –3SD/mean/+3SD theoretical value and deformation grid by TPS