International Journal of Industrial Ergonomics 19 (1997) 93–104

International Journal of
Industrial Ergonomics

An analysis of Kansei structure on shoes using self-organizing neural networks

Shigekazu Ishihara [a,*], Keiko Ishihara [b], Mitsuo Nagamachi [c], Yukihiro Matsubara [c]

[a] *Onomichi Junior College, 1600 Hisayamada, Onomichi, 722 Japan*
[b] *Hiroshima Chuo Women's Junior College, 3-1-15, Gion, Asaminami-ku, Hiroshima, 731-01 Japan*
[c] *Faculty of Engineering, Hiroshima University, 1-4-1, Kagamiyama, Higashi-Hiroshima, 739 Japan*

Abstract

Kansei engineering is a technology for translating human feelings into product design. Several multivariate analyses are used for analyzing human feelings and building rules. Although these methods are reliable, they require large computing resources. It is difficult for general users to deal with many variables because of small personal computers, and the need for the user to be an expert on statistics. This paper presents an automatic semantic structure analyzer and Kansei expert systems builder using self-organizing neural networks, ART1.5-SSS and PCAnet. ART1.5-SSS is our modified version of ART1.5, a variant of the Adaptive Resonance Theory neural network. It is used as a stable non-hierarchical classifier and a feature extractor, in a small sample size condition. PCAnet performs principal component analysis based on generalized Hebbian algorithm by Sanger (1989). These networks enable quick and automatic rule building in Kansei engineering expert systems. AKSYONN4 system is the automatic builder for Kansei engineering expert systems because it uses self-organizing neural networks. The system enables 'real-world' applications of Kansei engineering in product development.

Relevance to industry

An automatic analysis of human feelings on products and automatic building of Kansei engineering expert systems can increase the prospects of applying Kansei engineering to acceptable product design. Neural networks-based analysis and automatic expert system building enable the on-site analyzing.

Keywords: Kansei Engineering; Self-organizing neural network; Principal component analysis; Expert system; Semantic differentials

* Corresponding author. E-mail: pfg00672@niftyserve.or.jp, Fax: +81 848-22-5460; Tel.: +81 848-22-8311.

PII S0169-8141(96)00006-6

1. Introduction

Kansei engineering is a method used to convert a customer's ambiguous images of products into a detailed design (Nagamachi, 1988, 1991, 1995). Kansei is a Japanese word that corresponds to feeling or impression. Kansei engineering supports product designers by providing relations among customers' feelings and corresponding designs. It also assists the consumer in selecting a product that fits his/her feeling, among a variety of products.

The standard procedure of Kansei engineering involves: (1) Selection of adjective words for expressing Kansei on the products, (2) Kansei Experiment: Evaluation of the product samples using a semantic differential method (SD) scale questionnaire, (3) Multivariate analysis of evaluation data. The evaluation is often analyzed by principal component analysis (PCA) and Hayashi's Quantification Theory Type I. (4) Development of Kansei engineering expert systems. Obtained relations among components' design, feature and semantic structure are built into inference rules.

Our Kansei engineering expert systems (Kansei ES) can draw designs that correspond to the user's Kansei expressed by adjectives. We developed various Kansei ES for house interior design, car interior design, garment coordination, construction machine design and office chair design (e.g., Nagamachi, 1991, 1995, Horiguchi and Suetomi, 1995; Shimizu and Jindo, 1995; Jindo et al., 1995; Fukushima et al., 1995).

Statistical analysis and building expert systems require different kinds of expertise for each work. Because multivariate analyses have different mathematical constraints, it is not easy to use for ordinary industrial designers. Kansei engineering is regarded as an important technique; however, such difficulties are technical hurdles that kept the enabling tools from real-world industrial applications.

In recent years, we have developed several automatic analyzers and builder systems for Kansei ESs using self-organizing neural networks as a multivariate analyzer (AKSYONN: Automatic Kansei expert SYstem generator by self-Organizing Neural Network). These systems produce simplified Kansei ESs that have graphical user interfaces. They do not require any programming or statistical expertise. Applying self-organizing type neural networks to the analysis of Kansei experiment data enables easy, speedy and flexible analysis and rule building. In AKSYONN1 (Ishihara et al., 1993), product and adjective relations are extracted. In AKSYONN2 (Ishihara et al., 1994a), groups of adjectives that have similar meanings on products are extracted. In AKSYONN3 (Ishihara et al., 1994b), subjects' individual differences on Kansei experiment responses are extracted. All of the above systems use the ART1.5-SSS neural network as a classifier and a feature extractor.

In this article, we present AKSYONN4. This system performs an automatic analysis of the semantic structure of Kansei, by two types of self-organizing neural networks, PCAnet and ART1.5-SSS. PCAnet does principal component analysis, and ART1.5-SSS classifies PCA results and extracts features of each class. Our aim is automatic rule building on semantic structure of adjective words, instead of conventional PCA and interpretation of the computing results by well-trained statisticians.

Analyzed Kansei structure can give product designers several important insights in Kansei engineering. First, we identify adjectives that have similar meanings. By reducing those adjectives, we decrease the total number of adjectives used for the questionnaire. Thus, it makes the assessment easier, reduces the experimental load on subjects and achieves a more accurate assessment. Second, specifying Kansei structure shows explicit Kansei factors for product designs. AKSYONN4 obviously shows the structure of Kansei by two- or three-dimensional graphs. Engineers can easily grasp the Kansei structure, and can recognize important Kansei. Using these Kansei factors, design strategy will be more definite. In addition, prototypes and existing products can be classified (or mapped) on several Kansei factors. Both designer and engineer teams will recognize factors and will share ideas.

In the AKSYONN4 system, we reduced the amount of computation by using neural networks for the principal component analysis. Section 2 describes a measurement method of Kansei, principles and techniques for neural network-based analysis. The structure of the AKSYONN4 system is described in Section 3. Analyzing results of the Kansei experiment on shoes is detailed in Section 4. Section 5 presents comparisons with traditional multivariate analyses. In the comparison, our system shows that its analyzing ability is equal to conventional methods.

2. Analyzing Kansei structure

We regard Kansei as a set of many feelings, rather than a single feeling. The idea is derived from Osgood and his colleagues' works in the 1950s and early 1960s.

As we mentioned in a previous section, Kansei engineering uses SD method for modeling semantic space which shows relations between the sample and meanings of typical adjective words.

2.1. Semantic differential

The semantic differential was developed by Osgood et al. (1957) as a measurement technique to assess affective meaning. The semantic differential is a standardized procedure for eliciting a carefully devised sample of a subject's placement of a word on a continuum. It uses scales made of various polar terms. Subjects rate concepts against the series of 7- or 5-point scales. For example, subjects rate their meaning of 'Apple' along a scale of estimate terms (e.g., good_:_:_:_:_:_:_bad, large_:_:_:_:_:_small, active_:_:_:_:_:_passive). These scales provide quantitative measurements on different terms. By averaging across subjects, it can provide a stable estimation of the concepts.

Osgood and Suci (1955) assumed a general principal structure of meanings, and proposed doing factor analysis on ratings by semantic differential. They analyzed correlation matrices of ratings on estimate terms, and assumed extracted factors as axes of semantic space. By assigning estimate terms to the semantic space, we can recognize relations between meanings and concepts. If it can be demonstrated that some limited number of dimensions or factors are sufficient to differentiate among the meanings of randomly selected concepts, and if the scale system that is finally selected satisfies the usual criteria of measurement, then the data obtained with such a semantic differential become an operationally defined index of meaning. Osgood and his colleagues showed that semantic space can be abstracted by three orthogonal dimensions, Evaluation, Potency and Activity. Although they argued generality of the three dimensions, Osgood and others' later studies showed basic dimensions can change as evaluation varies (Osgood, 1962).

More than thirty years have passed from the proposal of semantic differential; yet, it is still the most powerful quantitative analyzing method of meanings, especially, for affective meanings. We have used the method for evaluating designs of products, and for analyzing semantic structures (Nagamachi, 1991, 1995).

2.2. Analyzing procedures in Kansei engineering

In Kansei engineering, evaluations are done on product samples. Estimate terms are taken from magazines, mail-order catalogues, and from recordings of conversations in stores. Some of these words are adjective words and others are jargon. We label these words as Kansei words.

After measurement by SD scales of many Kansei words, principal component analysis or factor analysis is used for compressing information into a smaller number of synthesized variables and for finding axes of semantic space. Then, Kansei words are mapped in the semantic space based on their principal component loadings. Similar Kansei words are grouped together. As a result, we obtain a basic structure of Kansei and word groups that have salient meanings on evaluation.

The structure of Kansei varies by the sort of products. Kansei structures of car interior design clearly differ from one of garment design. The constraints to products (e.g., functions, size, purpose) must relate specifically to the product design. Thus, we must analyze Kansei structure by principal component analysis, for every product using many Kansei words.

A common problem in doing principal component analysis is the requirement for large computer memory. Thus, even modern statistical analysis packages that run on powerful personal computers have a limit on a number of variables. Computation is often impossible because of the memory consumption of variables' correlation (or covariance) matrix and its operation. Moreover, doing multivariate analyses, building inference rules and building expert systems require expertise both on statistical and on artificial intelligence programming.

In this study, we used neural networks for analysis to reduce the problems of memory and expertise.

2.3. Principal component analysis by PCA net

As we mentioned earlier, multivariate analyses have an important role in Kansei engineering. When we deal with multivariate data whose variables are correlated, expressing a structure of the data by a smaller set of variables makes its explanation easier. Principal component analysis (PCA) is used to transform an original set of correlated variables into a new set of uncorrelated variables, which are linear composites of the original variables. This property of the analysis method is used to reduce an original set of variables to a smaller set, which accounts for much of the covariance in the original set, or to study the structure of a set of variables with underlying factors or sources of covariance. In other words, PCA summarizes most of the variation in a multivariate system in fewer variables. PCA is widely used among disciplines, such as psychology and computer science, as a tool for data compression and analyzing multivariate data structure.

Principal components are computed axes that provide minimum information loss. It provides generalized scales of combinations of many variables. Transforming sample scores by principal components (computing principal component scores), ranking and investigating characteristics of samples are achieved.

2.3.1. Principle of PCA

We describe the procedure of PCA in a qualitative manner. Suppose that there are p variables, $\{x_1, x_2, \ldots, x_p\}$. The aim is to get a linear compound that best summarizes the p-dimensional distribution. Fig. 1 geometrically shows an example of a solution.

Here, we define a new linear compound U_1, whose coefficients are $b_{11}, b_{12}, \ldots, b_{1p}$, thus, $U_1 = b_{11}x_1 + b_{12}x_2 + \cdots + b_{1p}x_p$. b_{1j} is defined so that the line U_1 represents the maximum variance. But it is not enough, because larger values of b_{1j} make the line U_1 have a larger variance, with no bounds. We

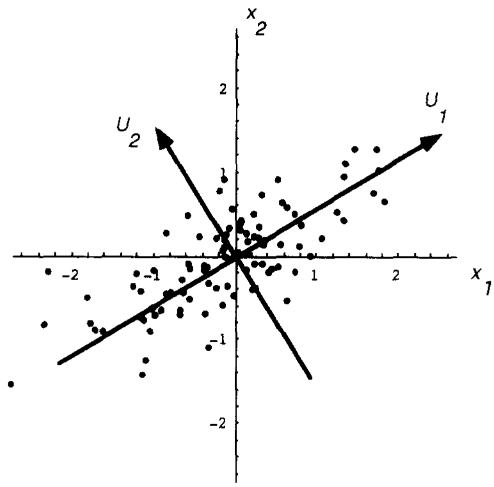

Fig. 1. A set of data and two principal components in the two-dimensinal plane.

constrain b_{1j} for $b_{11}^2 + b_{12}^2 + \cdots + b_{1p}^2 = 1$ to avoid this point. In this way, U_1 becomes a transformation to a specific line that represents the maximum variance of the p-dimensional set. The line is called the first principal component of variables $\{x_1, x_2, \ldots, x_p\}$. After getting U_1, the aim is to look for the linear compound U_2, that represents the next maximum variance. The constraints are that U_2 does not correlate with U_1 and is also normalized, that is, U_2 must be orthogonal to U_1. PCA seeks the hth line that represents the hth maximum variance after extracting lines from U_1, to U_h. We can approximate p variables data by a small number of principal components (Us) without large information loss. The Us are eigenvectors of the correlation matrix of the input $Q = E[xx^T]$. Jacobi method and QR method are conventional numerical computation methods for getting eigenvectors that are commonly used (Press et al., 1992).

A problem of the conventional method is consuming large memory. These methods must keep correlation matrix Q in memory and need iterative computation to convergence. This is one of the difficulties in doing PCA.

2.3.2. Hebbian learning rule and maximization of variance

We compute eigenvectors by a neural network. Here we assume a neuron y_1 that gets input signals from N neurons $x_1, x_2, \ldots, x_N$. c_{1i} is a synapse weight of x_i to y_1. Output signal of y_1 is defined as

$$y_1 = \sum_{i=1}^{N} c_{1i} x_i. \tag{1}$$

In a classical Hebbian learning rule, synapse weights are updated by Eq. (2).

$$c_{ji}(t+1) = c_{ji}(t) + \gamma y_j(t) x_i(t) \quad (\gamma\text{: constant}). \tag{2}$$

Following is an explanation for why the Hebbian rule maximizes the variance of output vector: When updating synapse weights, frequently inputted patterns add similar value to c_{1j}. As a result, such patterns come to have large influence to y_1. The inputs shown as dots in Fig. 1 have positive correlation between x_1 and x_2. In this case, most of the inputs have the same sign for x_1 and x_2 ([+,+] or [−,−]). As learning progresses, y_1 comes to have a large value when both x_1 and x_2 have large value and the same sign ([+,+] or [−,−]). Thus, the variance of y_1 is maximized in the direction to maximize the correlation between x_1 and x_2. This is similar to the procedure of eigenvector extraction of a correlation matrix in PCA. Each component of c can infinitely grow in the original Hebb rule. Oja proved that it is possible to make the sum of squares of each c converges to 1 by adding feedback. He also proved that $c_{11}, \ldots c_{1N}$ becomes the first eigenvector when converged (Oja, 1982).

2.3.3. Generalized Hebbian algorithm

Here we describe the Oja algorithm and the extension to extract second and more eigenvectors.

Eq. (3) shows the Oja algorithm. It finds only the first eigenvector which has the largest eigenvalue. Thus, Eq. (3) corresponds to the case of only one output (y_1) neuron.

$$c_i(t+1) = c_i(t) + \gamma y(t)[x_i(t) - y(t) c_i(t)]. \tag{3}$$

Sanger (1989) extended Oja's constrained Hebbian learning rule as generalized Hebbian algorithm (GHA). We define a single-layer network (one layer of processing neurons) $\vec{y} = C\vec{x}$, where $\vec{x}$ is the N-dimensional input vector, C is the $M \times N$ weight matrix, $\vec{y}$ is the M-dimensional output vector with

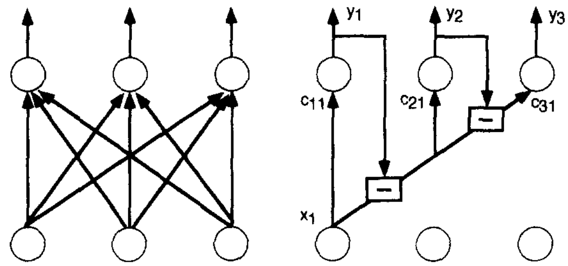

Fig. 2. Architecture of PCAnet (left) and network to implement learning rule (right).

$M < N$, and γ is the rate of changing the weights. In this paper, we regard network implemented GHA as a PCAnet. The architecture of PCAnet is shown in Fig. 2. The correlation matrix of the input is defined as $Q = E[xx^{\mathrm{T}}]$. GHA is described as:

$$c_{ji}(t+1) = c_{ji}(t) + \gamma(t)\left(y_j(t) x_i(t) - y_j(t) \sum_{k \le j} c_{ki}(t) y_k(t)\right). \tag{4}$$

Eq. (4) shows a modification rule for the synapse weight between the ith element of input vector and the jth neuron. Synapse weights and outputs of beforehand $(1, \ldots, j-1\text{th})$ neurons negatively affect the modification of jth neuron's weight. The GHA combines the Oja algorithm and Gram-Schmidt orthogonalization algorithm. It can extract M eigenvectors in order.

In this algorithm, if we maintain the diagonal elements of CC^{T} equal to 1 then a Hebbian learning rule will cause the rows of C to converge to the first eigenvector of Q.

The rows of C are the M eigenvectors of Q, $CC^{\mathrm{T}} = I$ and $Q = C^{\mathrm{T}}AC$, where A is the diagonal matrix of eigenvalues of Q in descending order. The weight adaptation process guarantees $CC^{\mathrm{T}} = I$. GHA provides a practical procedure to find M eigenvectors without calculating Q.

Fig. 3 shows the trajectory of c in the orthogonalization process. In this example, the center of distribution of the set of input data (shown as dots) is [0,0]. PCAnet has 2 neurons that have 2-dimensional input vectors. After 200 inputs, $c_{11} = 0.82$, $c_{12} = 0.63$, $c_{21} = -0.22$, $c_{22} = 0.62$ (shown as solid arrows). Two y neurons have mutually orthogonalized

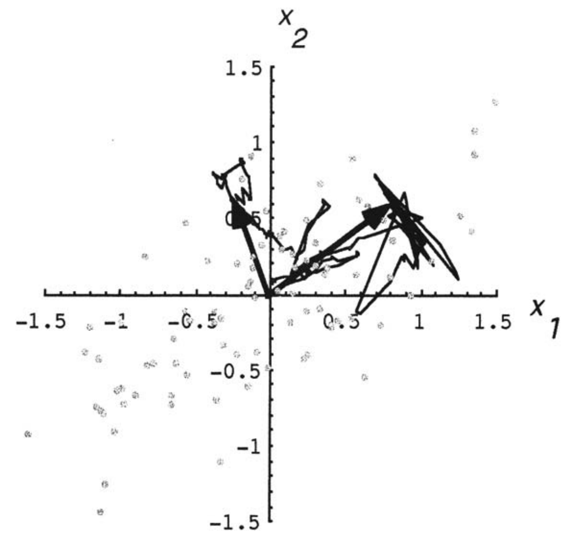

Fig. 3. Two principal components extracted by PCAnet.

synapse weights that correspond to first and second eigenvectors.

2.4. *Self-organizing clustering neural network, ART1.5-SSS*

In the preceding chapter we described computation of principal component loadings using synapse weights and output values of PCAnet. Dimensionality of variables is remarkably reduced. Furthermore, to classify Kansei words in abstracted semantic space by principal component loadings makes its explanation easier. ART1.5-SSS, another self-organizing neural network in AKSYONN4 system, does such a task. The network performs non-hierarchical self-organizing clustering. Since the mechanism of the network was already explained in Ishihara et al. (1995), we show its outline here.

In general, classifying input data into appropriate classes is an important aspect of recognizing the data. When a set of input data and its corresponding class (called teacher or correct answer) is given, the task is called 'learning with teacher' or 'supervised learning'. When only a set of input data is given, it is called 'learning without teacher' or 'unsupervised learning'. Hertz et al. (1991) noted several possibilities of unsupervised learning. Principal component analysis is one of them. Several output units construct a set of axes (principal components), along similarity to previous examples, with a kind of majority rule of inputs. As we mentioned in the preceding section, eigenvectors are formed in the weights of PCAnet.

Another possibility of unsupervised learning network is a self-organizing clustering network. Different from PCA, only one unit is active among output units at a time; the unit corresponds to a class which the input falls into. This type of neural computation is based on competitive learning where output units compete for being fired. A unit that has the largest inputs will be a winner. A class corresponds to an input which is found by the similarity to the previous examples. Similar inputs are classified into a same output unit which corresponds to a class. The classes must be made by the network itself from the set of input data. Self-organizing clustering means self-generation of classes. Learning is done on a winner unit to reflect inputs. As learning proceeds, a synapse weight vector of each output unit comes to a prototype of a class.

In simple competitive learning networks, an input must be classified into a winner output unit. The winner is merely the most similar one among the previous formed classes; thus, it is not convinced it is similar enough to a new input. ART is an extension of simple competitive learning to enable stable and accurate clustering. ART type neural networks have an explicit distance measurement mechanism and distance criterion r. In ART, a new input is given, when it is similar enough to a winner's prototype, then the prototype is slightly modified to the new input. When not similar enough to a winner, and when there ever exists an unassigned unit, the unassigned unit is chosen as a winner.

We used ART1.5-SSS (Ishihara et al., 1993, 1994a,b,c,1995). It has two layers (F1 and F2) which contain processing units and a reset mechanism. The neurons involved in F1 receive input signals. Each F2 neuron represents a class and is connected with inhibitory links to other F2 neurons. F1 and F2 units are interconnected. Through a competition process, one neuron is activated that receives maximum input signals multiplied by bottom-up synapse weights. (See Fig. 4.)

A reset mechanism sends a reset signal to the F2 layer when a prototype (top-down weights) and the

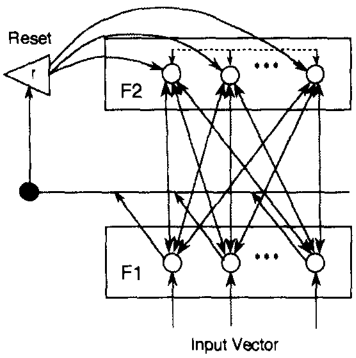

Fig. 4. Architecture of ART1.5-SSS.

input vector are not similar. Similarity is measured by an angle between two vectors. When the angle is smaller than similarity criterion, a match occurs. Otherwise, a reset signal is sent, and a search occurs.

When a search occurs, the algorithm selects the next maximum neuron and tests again. If all committed nodes failed the test, an uncommitted node in F2 is chosen for the new class.

Connections between the chosen neuron in F2 and the neurons in F1 are modified so that they become slightly similar to the input vector. Each top-down and bottom-up synapse weights vector of a class (each F2 neuron) can be interpreted as a prototype of input vectors that belong to the class. We modified the learning rule of ART1.5 (Levine and Penz, 1990) to make classes that have meanings under small sample size conditions. We call it ART1.5-SSS, and we confirmed its ability by comparing it with conventional cluster analysis and with MDS (Ishihara et al., 1995).

In this paper, we present the AKSYONN4 system that automatically analyzes SD questionnaire data by the two self-organizing neural networks discussed above. The neural networks analyze the data with less memory than conventional computing methods. In the next section we describe its architecture.

3. AKSYONN4 system architecture

The AKSYONN4 system takes Kansei experiment data as an input and generates Kansei ES on the target domain. It involves the rule generator and Kansei ES generator (see Fig. 5).

Rule generator. The rule generator that has PCAnet and ART1.5-SSS generates inference rules of relations between adjectives and the physical design of products, and rules of semantic structure. Both PCAnet and ART1.5-SSS are self-organizing type neural networks as described in the previous section. PCAnet performs principal component analysis. ART1.5-SSS is used for classifying adjective words by principal component loadings.

The rule building procedure is as follows.

1. Extract eigenvectors by PCAnet
   Evaluation values of k sample products by a SD questionnaire that contains n adjectives are encoded into k of n-dimensional vector set (averaged between subjects). When a user inputs a set of data, PCAnet extracts eigenvectors of a correlation matrix of n variables and computes principal component scores of product samples as output.
2. Compute principal component loadings
   Principal component loadings of each adjective are computed using eigenvectors and principal component scores. Since principal components are mutually orthogonalized, adjectives can be presented graphically on orthogonal space by principal component loadings. Principal component loadings and principal component scores are sent to ART1.5-SSS for classifying.
3. Classify adjectives and products by ART1.5-SSS
   ART1.5-SSS classifies adjectives into several groups by principal component loadings, so that members of each group have similar meanings according to the evaluation value on adjective words. It also classifies products by principal component scores.

Kansei ES generator. Kansei ES generator reads the output from the rule generator and automatically makes an expert system. The generated ES have card-type graphical user interface and each card shows classified Kansei words. It calls the picture data of each sample product and shows the picture data. Automatic generation of the ES can be completed in several minutes. The AKSYONN4 system is written by using C language, HyperTalk, that is a scripting language of HyperCard, and Mathematica. The system runs on a Macintosh computer.

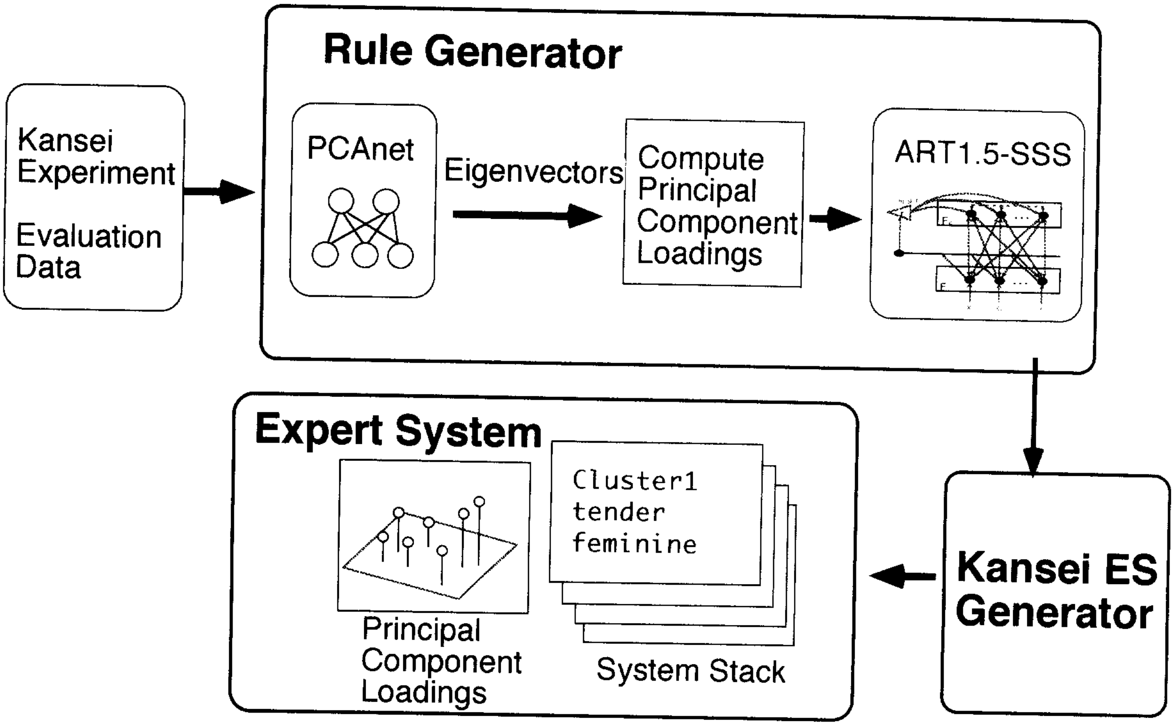

Fig. 5. Structure of AKSYONN4 system.

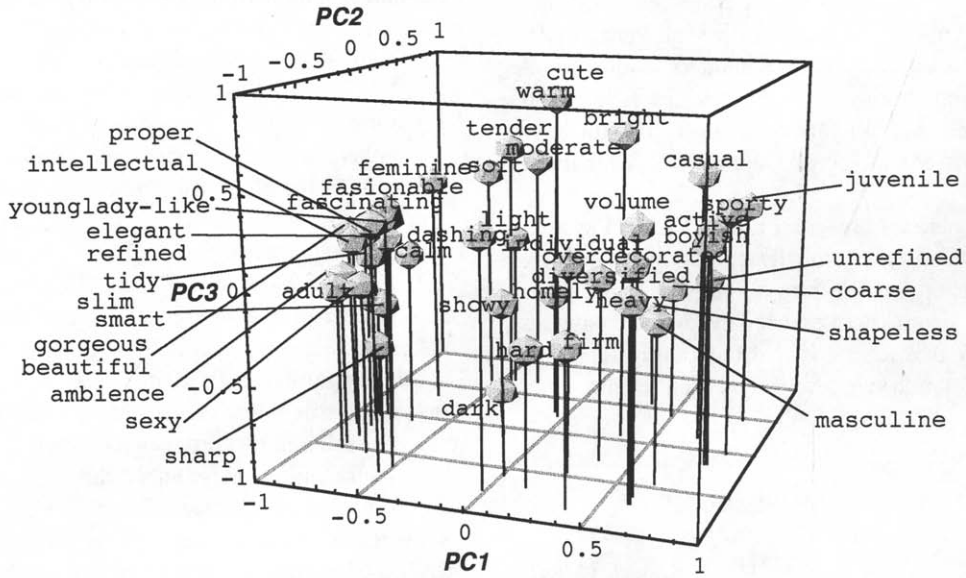

Fig. 6. Principal component loadings by PCAnet.

4. Analyzing Kansei semantic structure on shoes by AKSYONN4

We conducted an experiment for evaluating women's shoe (loafers and boots) samples on a 5-point SD scale. We selected 42 shoes from magazines and mail order catalogues. Pictures of shoes were processed to remove the background and their size and orientation were adjusted by image processing software. Processed pictures are presented to 18 female college student subjects whose ages were nineteen or twenty years. Forty-five adjective words were selected from articles by frequency of use, and used for evaluation on the SD questionnaire. Five-point scaled evaluations were encoded into 0.25 step values between 0 and 1. PCAnet computed eigenvectors and principal component scores of a set of data. (Initial value of γ is 0.02, data is given to network by 10 iteration.) Input vectors have 45 dimensions, and the number of neurons is four. Thus, four major principal components are extracted. Principal component loadings of each adjective are calculated from the variance of output of PCAnet. Fig. 6 shows the principal component loadings of each Kansei word from the first to third principal components.

On the first principal component (PC1), Kansei words that have positive large loadings are 'sporty', 'juvenile', 'active', 'boyish' and 'casual'. Words that have negative large loadings are 'elegant', 'slim', 'young ladylike', 'tidy'. The first principal component can be interpreted as an axis representing activity or refinement. On the second principal component (PC2), words that have positive large loadings are 'light', 'moderate', 'tender', 'soft' and 'shapeless'. Negative large words are 'hard', 'dashing', 'fascinating', 'heavy', 'over-decorated'. The second principal component can be interpreted as an axis representing solidity or heaviness. On the third principal component (PC3), positive large words are 'cute', 'warm', 'bright', 'casual' and 'tender'. Negative large words are 'dark', 'sharp', 'homely' and 'smart'. The third principal component can be interpreted as mildness and firmness.

Table 1
Classified Kansei words by ART1.5-SSS using principal component loadings by PCAnet

Cluster number	Kansei words
1	tidy, refined, elegant, young lady-like, smart, slim
2	adult, ambience, sexy, gorgeous, beautiful
3	homely
4	fascinating, fashionable
5	dashing
6	soft, light
7	moderate, feminine, tender, intellectual, calm, proper
8	warm, cute, bright
9	dark, shapeless
10	unrefined, coarse, juvenile
11	indivual, diversified, showy
12	sporty, casual, active, boyish, masculine, firm
13	volume, overdecorated, heavy, hard
14	sharp

ART1.5-SSS classified Kansei words by principal component loadings. Discrimination criteria variable r was 0.96. Kansei words are classified into fourteen clusters. Table 1 shows the cluster of Kansei words. Here we consider some of them. The words of cluster 1 have large negative loadings to PC1, small negative to PC2 and around zero value to PC3. Cluster 1 is regarded as words meaning highly refined and slightly heavy feelings. Cluster 12 is contrary to the cluster 1. The words of cluster 12 have large positive loadings to PC1, small positive to PC2, and around zero to positive on PC3. They mean not refined, light and active feelings. This contrast is mainly on PC1 and PC2. This is a major factor of Kansei on shoes. Cluster 11 and cluster 7 are contrary mainly on PC2. On shoes, appealingness is related to degree of solidity and heaviness.

Using two self-organizing neural networks, the semantic structure of Kansei is automatically analyzed. Kansei ES generator reads the analyzed results, and generates simplified ES that have graphical user interface. Users can browse and explore Kansei structures by the ES. Fig. 7 shows the screen of built Kansei ES.

5. Comparisons with conventional computation methods

To verify the analyzing ability of PCAnet and ART1.5-SSS, we compared the results to conventional computation methods.

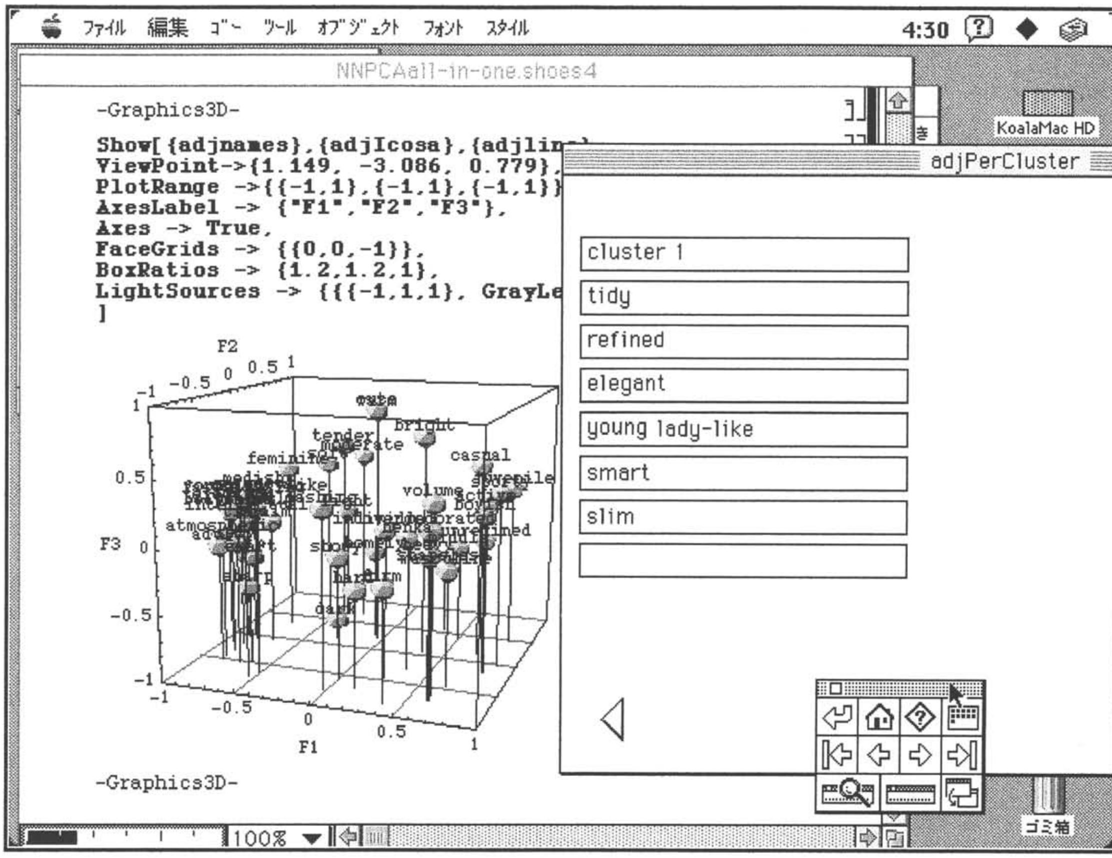

Fig. 7. Screen dump of generated Kansei ES.

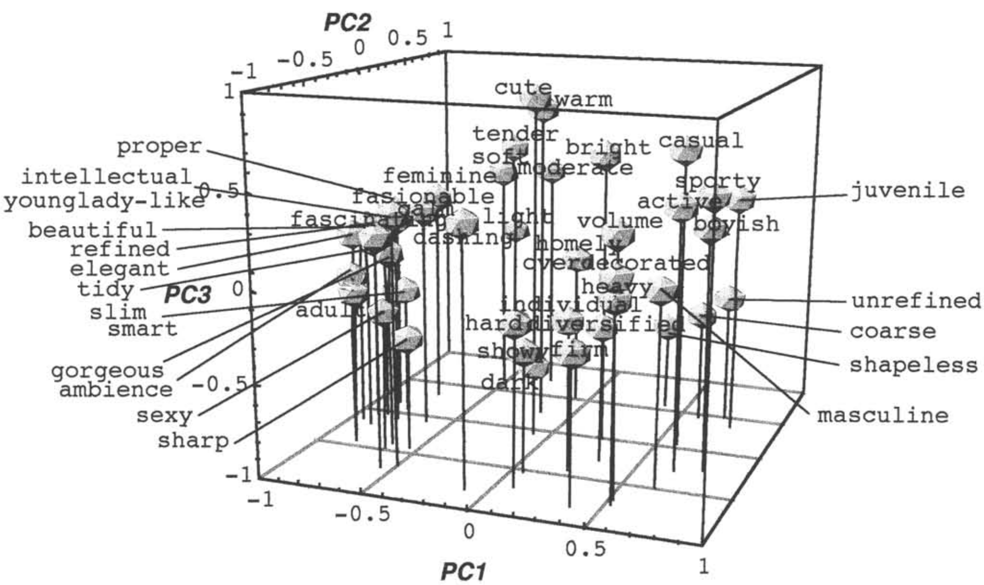

Fig. 8. Principal component loadings by QR method.

Table 2
Classified Kansei words by UPGMA using principal component loadings by QR method

Cluster number	Kansei words
1	tidy, refined, elegant, young lady-like, smart, slim, intellectual *, beautiful *, calm *, proper *
2	adult, ambience, sexy, gorgeous, sharp *
3	homely
4	fascinating, fashionable
5	dashing
6	moderate, feminine, tender, soft *, light *
7	warm, cute
8	bright *
9	dark
10	unrefined, coarse, shapeless *
11	indivual, diversified, showy
12	sporty, casual, active, boyish, juvenile *
13	volume, overdecorated, heavy, masculine *, firm *
14	hard *

We used QR method for the conventional method for PCA. The method is known as precise computation method of numerical eigenvectors and eigenvalues (see e.g. Press et al., 1992). Fig. 8 shows principal component loadings by QR method. Fig. 8 and Fig. 6 show similar results. Differences of principal component loadings on the principal component by the two methods are calculated. The maximum squared difference is 0.153; the mean value is 0.012. PCAnet based PCA result seems to be a good approximation of the conventional method.

Principal component loadings by QR methods are classified by the UPGMA method. UPGMA (unweighted pair group method using arithmetic averages) is one of the most commonly used hierarchical clustering methods (Romesburg, 1989). Table 2 shows the classification result. We decided a cut-off point of distance measure (0.6) in a dendrogram, where the number of clusters is the same as the result of ART1.5-SSS.

Marked (*) words in Table 2 are classified into different clusters from the neural network-based analysis result. Several words are classified into different clusters, and two clusters (cluster 6 and part of cluster 7 of ART1.5-SSS) were joined to cluster 6. It is well known that conventional clustering often shows different results by methods of similarity (or dissimilarity) measurement and methods of combining clusters (e.g., Anderberg, 1973; Romesburg, 1989). We compared several different clustering methods. The words differently classified are also classified into different clusters by other methods. We regard words that are located on the fringes of the clusters as unstable. Classification results by conventional methods and by ART1.5-SSS are practically similar.

6. Discussion

Comparisons of the analyzed results confirm the ability of our neural network based Kansei structure analysis. It is well known that clusters' boundaries are rather different by many clustering methods. Although comparison of accuracy is a relative one our approach shows sufficient accuracy.

Self-organizing neural networks that we used take less computation and can perform fast analysis. As Sanger (1989) notes, PCAnet does not need to contain a correlation matrix that takes much memory. Thus, in eigenvector extraction, it needs a smaller matrix computation than conventional methods.

In this study, we used 45 Kansei words. The correlation matrix Q contains 2025 elements, and requires prior computation for Q and containment throughout the computation process. PCAnet requires yx^{T} and yy^{T} matrices. In this experiment, the number of elements is $180 + 16$. Because the required number of principal components is less than the dimension of input vector, PCAnet can compute using smaller amounts of memory than conventional methods. This feature enables us to expand the number of expressing Kansei words for analysis using smaller computers and quick analyzing. It is preferable to use Kansei engineering ES on the site of the design.

7. Conclusions

We have developed a self-organizing neural networks-based automatic analyzer of Kansei semantic structures. Accuracy of the analyzer was confirmed by comparison with conventional computation methods of multivariate analysis.

We attempt to apply this system and continue to confirm its accuracy for many cases of Kansei experiments' data.

References

Anderberg, M.R., 1973. Cluster Analysis for Applications. Academic Press, New York.

Fukushima, K., Kawata, H., Fujiwara, Y. and Genno, H., 1995. Human sensory perception oriented image processing in a color copy system. International Journal of Industrial Ergonomics, 15(1): 63–74.

Hertz, J., Krough, A. and Palmer, R.G., 1991. Introduction to the Theory of Neural Computation. Addison-Wesley, Redwood City, CA.

Horiguchi, A. and Suetomi, T., 1995. A Kansei engineering approach to a driver/vehicle system. International Journal of Industrial Ergonomics, 15(1): 25–37.

Ishihara, S., Hatamoto, K., Nagamachi, M. and Matsubara, Y., 1993. ART 1.5-SSS for Kansei engineering expert system. In: Proc. 1993 Int. Joint Conf. on Neural Networks-Nagoya, pp. 2512–2515.

Ishihara, S., Ishihara, K., Matsubara, Y. and Nagamachi, M., 1994a. AKSYONN: Automated Kansei engineering expert system builder by self-organizing neural network. In: G.E.Bradley and H.W.Hendrick (Eds.), Human Factors in Organizational Design and Management-IV. North-Holland, Amsterdam, pp. 485–490.

Ishihara, S., Ishihara, K., Nagamachi, M. and Matsubara, Y., 1994b. Automatic analyzer for Kansei-product relations by self-organizing neural network. In: Proc. 12th Int. Ergonomics Association Congress, Vol.4, pp. 130–132.

Ishihara, S., Ishihara, K., Matsubara, Y and Nagamachi, M, 1994c. Self-Organizing neural networks in Kansei engineering expert system. In: Proc. 11th European Conf. on Artificial Intelligence. Wiley, Chichester, pp. 231–235.

Ishihara, S., Ishihara, K., Nagamachi, M. and Matsubara, Y., 1995. An automatic builder for a Kansei Engineering expert system using self-organizing neural networks. International Journal of Industrial Ergonomics, 15(1): 13–24.

Jindo T., Hirasago, K. and Nagamachi,M.,1995. Development of a design support system for office chairs using 3-D graphics. International Journal of Industrial Ergonomics, 15(1): 49–62.

Levine,D.S. and Penz,P.A., 1990. ART 1.5 – A simplified adaptive resonance network for classifying low-dimensional analog data. In: Proc. 1990 Int. Joint Conf. on Neural Networks, Washington, DC, Vol. 2, pp. 639–642.

Nagamachi, M., 1988. Image technology based on knowledge engineering and its application to design consultation. In: A.S. Adams, R.R. Hall, B.J. McPhee and M.S. Oxenburgh (Eds.), Proc. 10th Congress of International Ergonomics Association, pp. 72–74.

Nagamachi, M., 1991. An image technology expert system and its application to design consultation. International Journal of Human–Computer Interaction, 3(3): 267–279.

Nagamachi, M., 1995. Kansei Engineering: A new ergonomic consumer-oriented technology for product development. International Journal of Industrial Ergonomics, 15(1): 3–11.

Oja, E., 1982. Simplified neuron model as a principal component analyzer. Journal of Mathematical Biology, 15: 267–273.

Osgood, C.E. and Suci, G.J., 1955. Factor analysis of meaning. Journal of Experimental Psychology, 50(5): 325–338.

Osgood, C.E., Suci, G.J. and Tannenbaum, P.H., 1957. The Measurement of Meaning. University of Illinois Press.

Osgood, C.E., 1962. Studies on the generality of affective meanings systems. American Psychologist, 17: 10–28.

Press, W.H., Teukolsky, S.A., Vetterling, W.T. and Flannery, B.P., 1992. Numerical Recipes in C (2nd ed.). Cambridge University Press, Cambridge.

Romesburg, H.C., 1989. Cluster Analysis for Researchers. Robert E. Krieger Publishing, Malaber, FL.

Sanger, T.D., 1989. Optimal unsupervised learning in a single-layer linear feedforward neural networks. Neural Networks, 2: 459–473.

Shimizu, Y. and Jindo, T., 1995. A fuzzy logic analysis method for evaluating human sensitivities. International Journal of Industrial Ergonomics, 15(1): 39–47.