A HYBRID KANSEI ENGINEERING SYSTEM USING THE SELF-ORGANIZING MAP NEURAL NETWORK

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Abstract **- Kansei Engineering (KE), a technology founded in Japan initially for product design, translates human feelings into design parameters. Although various intelligent approaches to objectively model human functions and the relationships with the product design decisions have been introduced in KE systems, many of the approaches are not able to incorporate human subjective feelings and preferences into the decision-making process. This paper proposes a new hybrid KE system that attempts to make the machine-based decision-making process closely resembles the real-world practice. The proposed approach assimilates human perceptive and associative abilities into the decision-making process of the computer. A number of techniques based on the Self-Organizing Map (SOM) neural network are employed in the backward KE system to reveal the underlying data structures that are involved in the decision-making process. A case study on interior design is presented to evaluate the efficacy of the proposed approach. The results obtained demonstrate the effectiveness of the proposed approach in developing an intelligent KE system which is able to combine human feelings and preferences into its decision making process.**

Keywords: **Decision support system, Kansei Engineering, Self-Organizing Map, interior design.**

1. INTRODUCTION

Advanced methods of visualisation are crucial to uncover important structures and interesting correlations in data during the process of generating useful, meaningful, and even unpredictable information from the flood of data. König and Michel (2003), Yin (2002), Mao and Jain (1995), Cox and Cox (1994), and Siedlecki et al. (1988) describe many existing Artificial Neural Network (ANN) and machine learning models for data projection, and propose their own algorithms for similar purposes. Projection of multivariate data enables visualisation of the underlying structure of high dimensional data, exploration of the intrinsic dimensionality, and analysis of the clustering tendency of multivariate data (König & Michel, 2003). Indeed, visualisation can lead to a better understanding of the underlying data structure as it takes advantage of human's perceptive and associative abilities to perceive clusters and correlations in data analysis.

Feature extraction and projection of multivariate data, on the other hand, helps visualize high dimensional data, provides a better understanding of the underlying data structure, explores the intrinsic dimensionality, and analyses the clustering tendency of multivariate data (Mao & Jain, 1995). Feature extraction as well as multivariate data projection and visualization have become a topic of research since the 1970's (Sammon, 1969; Sammon, 1970). This area of research continues to gain interest owing to the enormous amount of data generated by rapidly growing databases and related computational resources. Advanced methods of pattern recognition, data analysis, and visualization are becoming crucial to uncover important structures and interesting correlations in data in the effort to generate useful, meaningful, and even unpredictable information from the flood of data (Jain et al., 2000)

Kansei Engineering (KE) (Nagamachi, 1999) is a well-known ergonomics technology that enables a customer's image and feeling to be incorporated into new products and subsequently produces products that fit the customer's image. A forward KE system, which serves as a consumer decision support system, enables the consumer to obtain the desired product design by providing appropriate Kansei word(s) to the system. A backward KE system, on the other hand, serves as a designer decision support system. In the backward KE system, a designer draws a rough sketch as a design input into the computer in which the computer system will recognize and classify the pattern of the design input. A system that combines both the forward and backward KE systems is known as a hybrid KE system.

Earlier applications of KE have very much been based on statistical methods to analyse data and to infer the Kansei rules. Yang et al. (1999) proposed a rule-based inference model to translate human Kansei into design elements. Other methods, such as back-propagation neural networks (Hsiao & Huang, 2002), genetic algorithm (Tsuchiya et al., 1999) and ART-based hierarchical clustering (Ishihara et al., 1995) have been incorporated into KE systems to improve the data analysing process. All these researches mainly focus on the analytical approach that models the human functions and the relationships with the product design decisions.

The main objective of this work is to investigate how to exploit human subjective abilities in a hybrid KE system. It highlights a few techniques that aim to assimilate human observers' perceptive and associative abilities into the decision-making process of the computer in an effort to make the whole decision-making process mimics the real world practice. Specifically, this paper proposes the use of the Self-Organizing Map (SOM) (Kohonan, 1982) neural network as a multivariate data projection and visualization method for mapping high dimensional data vectors to a two-dimensional space in a hybrid KE system. Besides, methods on how SOM can be used for clustering and feature extraction are also shown. The incorporation of a three-dimensional desktop virtual reality facility into the system has also provided another interesting perspective to the user, which is illustrated in the case study on bedroom colour scheme perception.

The organization of this paper is as follows. In section 2, a description on the SOM neural network and the KE system is presented. To evaluate the effectiveness of the proposed system, a case study on interior design is presented in Section 3. The detailed results, analysis, and discussion of the case study are also included. A summary of concluding remarks and suggestions for further work is presented in Section 4.

2. SELF-ORGANIZING MAP AND KANSEI ENGINEERING SYSTEM

2.1 The Self-Organizing Map

SOM is a neural network model that has been used in a wide variety of applications (Kohonen, 1997). The model can be viewed as a computational mapping principle that forms an ordered nonlinear projection of high-dimensional input data samples onto a regular low-dimensional, usually two-dimensional, grid. The model has been used in a lot of areas especially for visualisation and clustering of data (Van Hulle, 2000).

The basic sequential training procedure of SOM starts with a formation of N unit grid points (also called nodes) on a regular low-dimensional, usually two-dimensional, grid. Each node j has an associated d-dimensional prototype vector $\mathbf{w}_j = (w_{j1}, w_{j2}, \cdots w_{jd})$, where j is the index of the node. The lattice type of the array can be defined to be rectangular or hexagonal. At each training step t, an input vector, $\mathbf{x} \in V$, with $V \subseteq R^d$, is randomly chosen from the training set. The distance between $\mathbf{x}$ and all the prototype vectors are computed. The smallest of the Euclidean distance $\|\mathbf{x} - \mathbf{w}_j\|$ defines the Best Matching Unit (BMU), signified by i^*:

$$i^* = \arg\min_i \|\mathbf{x} - \mathbf{w}_i\| \tag{1}$$

The winning unit or BMU and its neighbours adapt to represent the input further by modifying their reference vectors towards the current input. The amount the units learn is governed by an unsupervised competitive learning rule:

$$\mathbf{w}_j(t+1) = \mathbf{w}_j(t) + \eta h_{i^*j}(t)[\mathbf{x}(t) - \mathbf{w}_j(t)] \tag{2}$$

with η the learning rate (a small positive constant) and the neighbourhood function h is a decreasing function of the distance of the units from the winning node on the grid. If the locations of units i and j on the map grid are denoted by the two dimensional vectors $\mathbf{r}_i$ and $\mathbf{r}_j$, respectively, then the Gaussian neighbourhood function h is defined as:

$$h_{i*j}(t) = \exp\left(-\frac{(\mathbf{r}_{i*} - \mathbf{r}_j)^2}{2(\sigma_\Lambda(t))^2}\right) \tag{3}$$

with $\mathbf{r}_i$ and $\mathbf{r}_j$ the lattice coordinates of neuron i^* (winner) and j, of which the range $\sigma_\Lambda(t)$ decreases as follows:

$$\sigma_\Lambda(t) = \sigma_{\Lambda 0}(t)\exp\left(-2\sigma_{\Lambda 0}\frac{t}{t_{\max}}\right) \tag{4}$$

with t the present time step, $t_{\max}$ the maximum number of time steps, and $\sigma_{\Lambda 0}$ the range spanned by the neighbourhood function at t=0. The radius of the neighbourhood range $\sigma_{\Lambda 0}$ at the beginning of the process may be selected as fairly large (rough training), and put to shrink monotonically in further iterations (fine training).

The weight update process in SOM is performed using an incremental learning scheme. The training procedure can further be optimised by using batch learning. In batch learning, the weight is updated after all input samples of the training set are considered. The following section explains the details of the SOM batch map-learning model.

2.2 The SOM batch map model

The batch map (Kohonen & Somervuo, 2002) is a variant of SOM that is based on a fixed-point iteration process. Instead of using a single data vector at a time, the whole data set is presented to the map before any adjustment is made. It provides a considerable speed-up to the original SOM training procedure by replacing the incremental weight updates with an iterative scheme that sets the weight vector of each neuron to a weighted mean of the training data. The initial values of the prototype vectors $\mathbf{w}_j$ may be randomly selected, preferably from the input samples (Kohonen & Somervuo, 2002). The SOM batch map-learning algorithm is as follows:

Given a fixed training set $M=\{\mathbf{x}^\mu\}$ of M input samples, μ=1,2..,M, compare each $\mathbf{x}$ with all $\mathbf{w}_j$, j =1,2,...N, and copy each $\mathbf{x}$ to the sublist associated with the map unit that has the shortest Euclidean distance. When all $\mathbf{x}^\mu$ are distributed into the respective sublist of the map units (see Figure 1), the new weight vectors are computed according to:

$$\mathbf{w}_j(t+1) = \Big(\sum_{\mu\in M} h_{i*j}(t)\mathbf{x}^\mu\Big) \Big/ \Big(\sum_{\mu\in M} h_{i*j}(t)\Big) \tag{5}$$

where i^* is the BMU of all data vectors as in Equation (1).

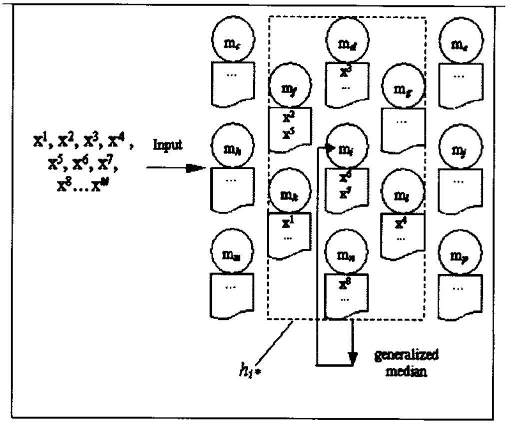

Figure 1: Illustration of the SOM batch learning process (adapted: Kohonen & Somervuo, 2002)

The new weight vector is a weighted average of the data samples, where the weight of each data sample has the neighbourhood function value $h_{i^*j}(t)$ at its BMU i^*, i.e.,

$$h_{i^*j}(t) = \exp(\frac{-(\mathbf{r}_{i^*} - \mathbf{r}_j)^2}{2(\sigma(t))^2}) \tag{6}$$

where $\mathbf{r}_{i^*}$ and $\mathbf{r}_j$ represent the lattice coordinates of neurons i^* and j, and $\sigma(t)$ is the neighbourhood range at the t-th training epoch. At every iteration, each weight vector is replaced by the generalized median of the input data assigned to the sublist in the map. The procedure is repeated until the maximum of t_{max} step is reached.

2.3 Kansei Engineering (KE) Systems

Kansei Engineering, which was founded by M. Nagamachi of Hiroshima University, is a technology that enables a customer's image and feeling to be incorporated into new products, and also produces products that fit a customer's preferences. There are two major types of KE systems (Nagamachi, 2002), i.e. forward and backward KE systems. In a forward KE system, which serves as a consumer decision support system, the consumer obtains the desired product design by providing appropriate Kansei word(s) to the system. The backward KE system, on the other hand, serves as a designer decision support system. In the backward KE system, the designer draws a rough sketch as a design input into the computer in which the computer system will recognize and classify the pattern of the design input. A system that comprises of these two types of KES, known as a hybrid KE system (Nagamachi, 2002), is shown in Figure 2.

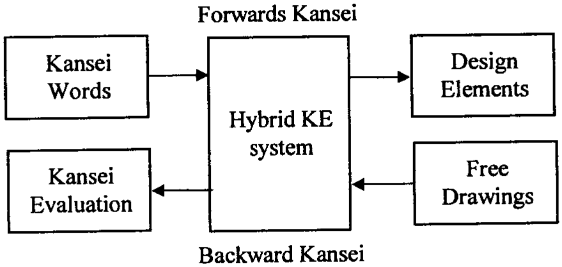

Figure 2: A schematic diagram of a hybrid KE system (adapted: Nagamachi, 2002)

In this work, a hybrid KE system for designing the bedroom colour scheme has been developed. Through the forward KE system, rules are obtained and databases are built. In addition, a computer user interface, which includes the use of a 3-D virtual environment to provide a more realistic 3-D look of the bedroom, is developed to assist in the designing process. Indeed, the measurement and analysis methods employed in this forward KE system are almost similar to those suggested by Nagamachi (2002). However, unlike most other backward KE systems, this work demonstrates the use of SOM to provide multivariate data projection and feature extraction in the backward KE system. A detailed elaboration of both forward and backward KE systems is provided in the subsequent sections.

3. A CASE STUDY ON INTERIOR DESIGN

The efficacy of the proposed hybrid KE system was evaluated using a case study on interior design, i.e., design of the bedroom colour scheme. In the forward KE system, the rules and the databases were produced. In addition, a computer user interface, which included the use of desktop virtual reality system to provide a realistic 3D appearance of the bedroom, was developed for the design process. The measurement and analysis methods employed in this forward KE system were almost similar to those suggested in Nagamachi (1999).

However, unlike most backward KE systems, this application demonstrated the utilization of SOM to perform data visualization and feature extraction in the backward KE system. This paper provides a detailed elaboration of the backward KE system that highlights the projection of high-dimensional data vectors to a lower dimensional space, generates different visualization methods, and extracts interesting and useful features from the pool of data by the designer or user of the backward KE system.

3.1 Three-dimensional virtual environments

There are various techniques for displaying designs on a computer system, such as text information, 2D image and texture, and 3D modelling or virtual reality/environment technology. A non-immersive virtual reality environment using a personal computer was developed to present the virtual bedroom model in this study. The VRML (Virtual Reality Modelling Language), a platform-independent language for describing three-dimensional interactive virtual worlds, was used. Figure 3 illustrates the virtual bedroom used in this study. This user interface enabled a user to walk-through the virtual space and to observe the model from different viewpoints.

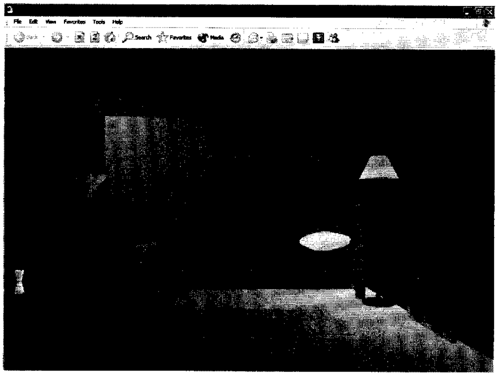

Figure 3: Example of a non-immersive virtual bedroom model on the web page

3.2 Forward KE System

A total of thirty adjectives were used for determining Kansei expressions of a bedroom. Each of these words was paired in an opposite pattern on a 5-grade semantic differential (SD) scale. Ten university students participated in the evaluation of twenty 3D virtual bedroom designs. Each participant was required to examine each of these bedrooms and provided their ratings for each of the thirty Kansei words on the SD scale.

The Principal Component Analysis (PCA) was then performed on the data collected from the evaluation. By employing PCA, axes of the semantic space (Kansei words) were obtained and the basic structures of Kansei that have salient meanings from the evaluation were grouped. The PCA produced four major axes. Table 1 summarizes the contribution of each axis and Table 2 lists the four groups of Kansei words for each principal component.

Table 1. Four major axes of PCA and contribution value of each axis (stated as a percentage)

		PC1	PC2	PC3	PC4
Hard-looking	Soft-looking	-0.2463	-0.1192	-0.0543	**0.1814**
Bright	Dull	0.1432	**0.1817**	0.0184	-0.0835
Modern	Old-Fashion	0.1479	**0.1822**	0.0247	0.1341
Relaxing	Tense	-0.1941	-0.1992	**0.3986**	-0.1443
Romantic	Not Romantic	**0.2292**	-0.1885	0.1112	0.1474
Soft-looking	Hard-looking	0.1491	0.0630	**0.1351**	-0.2418
Active	Quiet	0.0393	-0.3500	-0.0874	**0.4205**
High-Class	Low Class	-0.1650	**0.2670**	0.1137	-0.0798
Cool	Warm	**0.2027**	-0.2114	0.1152	-0.1586
Artistic	Not Artistic	-0.1866	**0.2925**	0.0764	-0.2595
Warm	Cool	-0.2457	0.0880	0.1227	**0.3370**
Calm	Stress	**0.2104**	-0.1956	0.1340	-0.1140
Comfortable	Not Comfortable	-0.1770	-0.1744	**0.3702**	-0.0860
Simple	Complicated	-0.2729	-0.0969	**0.1343**	-0.3183
Clean	Messy	**0.1822**	-0.0006	-0.0119	-0.0558
Elegant	Not Elegant	0.1379	0.0771	0.1302	**0.2367**
Contribution (%):		55.1	29.2	13.5	0.4
Cumulation (%):		55.1	84.3	97.8	98.2

Table 2. Four groups of Kansei words for each principal component

PC1	PC2	PC3	PC4
Romantic	Artistic	Relaxing	Active
Calm	High Class	Comfortable	Warm
Cool	Bright	Soft-looking	Elegant
Clean	Modern	Simple	Hard-looking
(Group 4)	(Group 3)	(Group 2)	(Group 1)

3.3 Backward KE System

Unlike most other backward KE systems (Matsubara & Nagamachi, 1997) that utilize information derived from the forward KE system, an alternative set of data was collected for the backward KE system in this study. The number of bedroom designs used during the evaluation for the forward KE system, i.e., twenty designs in total, was insufficient to provide representative input to the backward KE system.

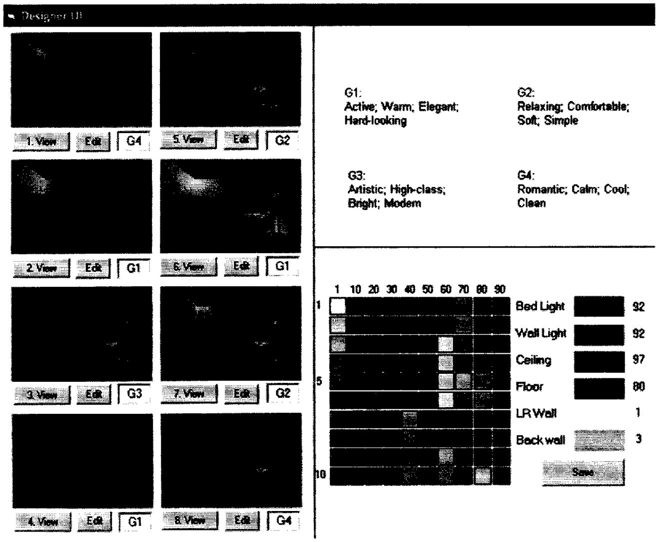

Figure 4: Computer-based bedroom color scheme design interface

Fifty university students (28 females and 22 males) were involved in the second evaluation. A computer-based design tool was developed for this purpose. Each student was required to explore and interactively change the colour of 6 variables of a virtual bedroom (bed light, wall light, ceiling colour, floor colour, left-right wall colour, and backdrop colour). The aim was to design a bedroom that suited a chosen Kansei or feeling. A total of 4 Kansei groups (in Table 2) that had salient meanings from the evaluation of forward Kansei were used in this study. Each student produced 8 bedroom designs, two for each of the four Kansei groups. Thus, a total of 400 bedroom designs were collected through this process.

A screenshot of the interface used in the design process is shown in Figure 4. The colour scheme for all the variables that conformed to a particular Kansei group was displayed on the right side of the interface. This colour scheme served to provide initial design ideas to the students. Nevertheless, they were free to choose different colour schemes from the ones suggested.

3.4 Visualization of cluster regions

The SOM model can be used for both non-linear data projection and visualization of cluster information. An initial idea of the number of clusters in SOM as well as their spatial relationships is usually acquired through a visual inspection of the map. Cluster borders can be determined between neighbouring regions in the map. In this case, the SOM enabled the visualization of the cluster (or density) structures of the data.

The unified distance matrix (U-matrix) method (Ultsch, 1993) was used as the measure of the local clusterness of the data. This method computes each map location and plots as grey levels on the map. Since it is known that the density of the prototype vectors reflects the density of the data points, the distances between neighbouring prototype vectors reflect the density. As a result, the probability density of the data was made visible to the user to provide them an idea of the overall distribution and possible cluster structures within the data set.

Figure 5 shows the U-matrix of the prototype vectors produced by SOM with a resolution of 20x20 units. This figure illustrates how the U-matrix technique provided an overview and general understanding on the nature of the data, and allowed the clusterness to be explored visually before extracting further information from each cluster.

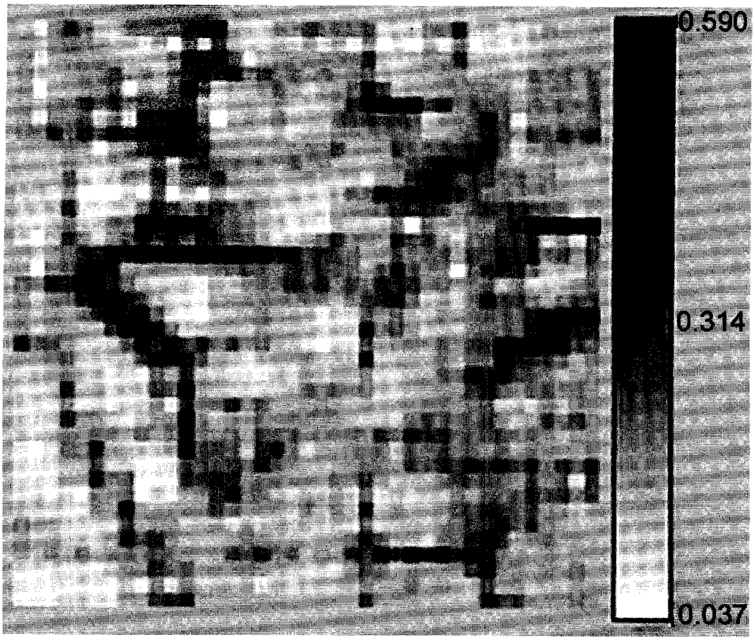

Figure 5: U-Matrix of the SOM map – the lighter areas shows the region for different clusters and dark stripes defines the borders of the clusters. The gray colour bar on the right shows the index of the relative distance between neighbouring prototype vectors.

3.5 Visualization of cluster regions and borders

Displaying the BMU of each data sample on the map provides another visualization method. In this case study, the class with the smallest Euclidean distance to the winning neuron, formed the label for each BMU. Figure 6 shows the labels obtained from the training data set that provided another obvious distinction of the various regions on the map. Overlaying Figure 6 on Figure 5 reveals the cluster regions and borders on the SOM map (shown in Figure 7).

2			2		2		2	2	1	1	4	3	3		3	3	3		3
	1	1	1		2					1	4	3	3		3	3	3	3	3
1	2	1	1	1			2			2			3		3	3	3		4
	2		2			3	2		2	3				4			4		3
2		1					2	4	2		3	3	3	4		3	3		3
1		1	1		2			2		2					3		3	3	3
1			1			2		2		3	3				4	4			3
1	1							3	3	3		4		4				3	4
				2							3	3	3	3	3			4	
2		1				2		2		3	3	3		3	3		4		3
	1	1	1		2				4	2	3		3	3	3	3	3		3
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1			1	2													4		
1	1	1	1	1	2		2	2	4	4	4		4		4		4		4

Figure 6: Labelling of BMUs on the SOM grids. Kansei groups 1-4 are used as labels

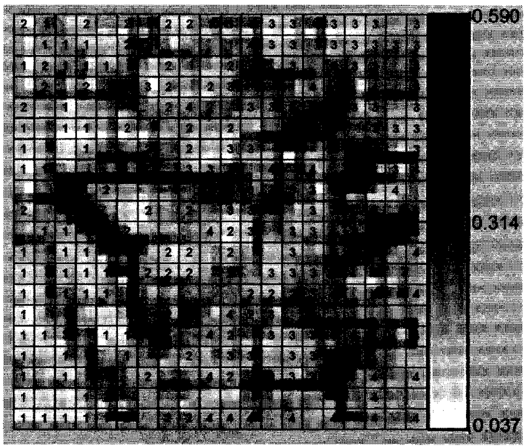

Figure 7: Overlaying U-matrix and BMU labels

3.6 Pattern classification

In the backward KE system, another user interface to examine the new bedroom design was developed. This interface was useful for a designer/user to know the Kansei group that a particular design belonged to. Based on each new design entry, the system determined the BMU. From the BMU label, the design was classified into the respective Kansei group. However, when the BMU did not have an associated cluster label, the design was considered novel.

Figure 8 shows the screenshot of the user interface. A new design input was given, and the design was classified as belonging to Kansei Group 1. The system also informed the user that four existing designs similar to this design were available. The colours were labelled based on the Web spectrum index provided by the Adobe® Photoshop® 7.0 image editing software.

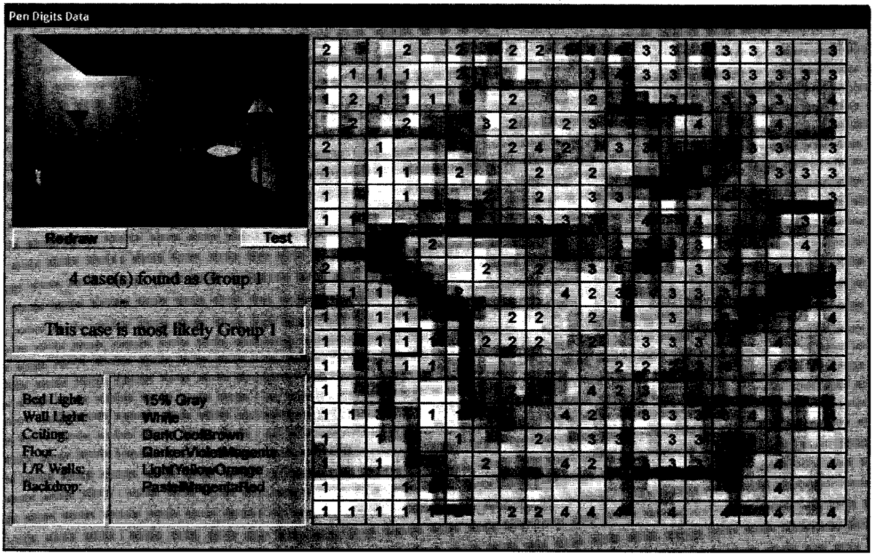

Figure 8: User interface for classifying a new bedroom design into one of the Kansei groups.

3.7 Extraction of cluster characteristics

After the labelling process, the SOM map was used to analyse and extract the Kansei clusters formed from the training data set. The designer was able to capture the preferred colour schemes for all the variables of each Kansei cluster by analysing the cluster information. The method employed was to find the median of each variable from the prototype vectors on the SOM map. For example, Figure 9 shows that seven clusters were identified visually by the designer on the SOM map. The median of the prototype vectors in each circle was selected and was used to generate the respective three-dimensional virtual bedroom.

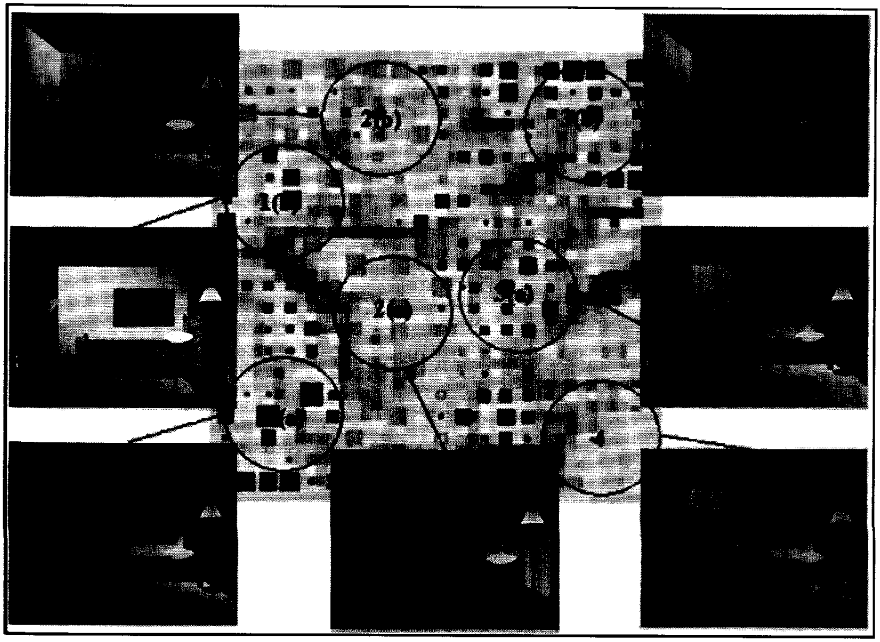

Figure 9: Group 1(a & b) -Active, Warm, Elegant, Hard-looking. Group 2(a & b) -Relaxing, Comfortable, Soft, Simple. Group 3(a & b) -Artistic, High Class, Bright, Modern. Group 4 –Romantic, Calm, Cool, Clean.

The next step was to measure the contribution of each variable in the cluster structure within an area of the map. The purpose was to summarize the characteristics of the clusters. As suggested by Siponen (2001), the interpretation of the clusters was aimed at understanding the components or variables important for each cluster; both within the cluster and with respect to other clusters. The measure of this compares the relative values of the variables for each cluster, and this can be computed using:

$$S_v(i,k) = \frac{\overline{w}_{ik} - \min_k}{\max_k - \min_k} \tag{7}$$

where $\overline{w}_{ik}$ is the mean value for variable k in cluster i, and $\min_k$, $\max_k$ were the minimum and maximum values of variable k. Equation (7) provides a measure of the relative importance of the variables within each cluster. However, it did not take other clusters into account. In order to consider other clusters, a second measure as shown in Equation (8) is used:

$$S_{\hat{v}}(i,k) = \frac{S_v(i,k)}{\frac{1}{C-1}\sum_{j \neq i} S_v(j,k)} \qquad (8)$$

Equation (8) gives a measure on how large the value of variable k relative to its value in other clusters. Both S_v and $S_{\hat{v}}$ are maximized in order to find the most significant variable.

Tables 3 and 4 show the relative importance of the variable within and across clusters. In Table 3, the colour of the floor and left/right walls in cluster 1(a) and 1(b) (Active, Warm, Elegant and Hard-looking) had the most significant values as compared with others variables within the same cluster. On the other hand, bed light, wall light, and ceiling colour were more important (on average) in cluster 2 (a) and (b) (Relaxing, Comfortable, Soft-looking, Simple) when compared with other clusters as depicted in Table 4.

Table 3. Relative importance of the variables within each cluster

Cluster	Bed Light	Wall Light	Ceiling	Floor	L/R Wall	Backdrop
1(a)	0.44	0.16	0.46	0.63	0.49	0.61
1(b)	0.43	0.62	0.23	0.51	0.70	0.42
2(a)	0.70	0.64	0.40	0.56	0.37	0.42
2(b)	0.62	0.59	0.82	0.55	0.58	0.35
3(a)	0.29	0.58	0.37	0.39	0.47	0.34
3(b)	0.73	0.44	0.51	0.44	0.59	0.81
4	0.54	0.53	0.65	0.61	0.84	0.43

Table 4. Relative importance of the variables between clusters

Cluster	Bed Light	Wall Light	Ceiling	Floor	L/R Wall	Backdrop
1(a)	0.80	0.29	0.92	1.24	0.83	1.32
1(b)	0.78	1.25	0.44	0.97	1.25	0.84
2(a)	1.37	1.31	0.79	1.08	0.61	0.84
2(b)	1.19	1.20	1.86	1.05	1.00	0.70
3(a)	0.51	1.17	0.73	0.71	0.79	0.68
3(b)	1.45	0.85	1.04	0.81	1.02	1.90
4	1.01	1.05	1.40	1.18	1.58	0.88

4. CONCLUSIONS

This paper proposes a number of approaches to increase the transparency of the decision-making process using the proposed backward KE system, which is conventionally performed solely by a computer system. As can be seen from the case study, the projection of data onto a two-dimensional map, the use of the visualization method, and the extraction of important features provide the support to highlight the underlying structures and correlations of data. Such approaches enable human subjective judgments to be assimilated into the decision-making process. With such assimilation, the deficiencies of a computer system can be mitigated by human subjective intelligence and, at the same time, the deficiencies of humans in information processing can be mitigated by system objectivity (e.g. classification). Indeed, as long as the computer system is still unable to model human subjectivity, devising approaches that enable the assimilation of human feedback into the decision-making process is indispensable in order to achieve a decision-making process that mimics the real-world practice.

In this paper, a pragmatic approach has been adopted to demonstrate the effectiveness of SOM for data visualization and classification. The visualisation map formed in SOM is in a regular shape. Nevertheless, this rigid grid has its limitations. When the data cloud is discontinuous, interpolating units are positioned between data clusters. In terms of visualisation, these may give false cues of the data shape, and should therefore be de-emphasised. Although the map is typically rectangular in shape, the axes of the map grid rarely has any clear interpretation. One way of improving the visualisation map is to provide an interactive visualisation environment that enables a user to navigate into the projection process, such as providing zoom functions in the navigation window. Such a feature will allow the user to interactively explore the data structure from a global to local perspectives. Thus, future work may explore this interactive feature to identify mapping faults as well as to produce accurate and meaningful visualisation.

5. REFERENCES

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