Development of an Intelligent Fabric Retrieval System using Computer-Based Kansei Algorithm

M. D. Shieh, C. C. Cheng

Department of Industrial Engineering, National Cheng Kung University, Tainan, Taiwan, R.O.C

Abstract: The objective of this research is to develop an intelligent fabric retrieval system using computer-based Kansei algorithms to assist fashion designers in designing costume textiles, as well as to help consumers find their preferred textile samples quickly and efficiently. The fabric retrieval system, based on human psychological Kansei and perception, can stimulate and increase the creativity of textile designers and other visual artifact designers alike. The fabric retrieval system is able to assist designers in creating new ideas through two ways interactively. The first is the high-level Kansei searching algorithm, where predefined impression words are systematically adjusted. The other is the low-level perception query, which includes perception feature modification and image similarity indexing. Moreover, the two ways are correlated with each other through a Neural Network. That is, the change of the values of low-level perception features, by users, could affect those of the Kansei features and the vision features of images simultaneously. Subsequently users could retrieve similar samples based on the impression words or vision features in this content-based retrieval system with a fabric database.

***Key words*:** *Fabric, Retrieval System, Neural Network, Kansei Engineering, Database*

1. Introduction

Until recently, thus studies for automatic estimation of retrieval keys to images based on image characteristics have been made. Early literature emphasizes upon "fully automated systems" and tries to find a "single best feature." [1] But such an approach is not necessarily the key to success, as computer vision technology is not quite there yet. In more recent research, growing emphasis is given to "human in the loop" and "interactive systems", than ever before, which is why it is important for computers to deal with human factors in this so-called "Era of multimedia".

In this paper, a high-level factor space of human impression that is common to textile images is established and a low-level feature space of image vision is defined. The mapping relationship between those two spaces is also obtained. We propose to establish the computer-based Kansei algorithm[2-4] and its application in image retrieval systems to assist fashion designers when designing textiles, as well as to help the consumer find textile samples that interest them. This can be done through correlating the low- level features, like color composition of textile images, with the high level features of human feelings, defined by impression words.

There are two major research aspects in our work: The first one addresses the issue of how humans perceive and measure similarity within the domain of the Kansei of images. To understand and explain this mechanism, we performed a subjective experiment. We used the SD method to find humans' impressions of various textiles, and through the ***Principle component analysis*** [4]we structured the factor space of a pyschological domain. By conferring the results of ***Hierarchical Cluster Analysis*** and the ***Multidimensional scaling (MDS)*** [5]from the experiments, the suitable features of images that influence human Kansei feelings are discussed. The next step is to define the feature space of images according to the suitable features obtained from the first step. The two feature vectors, which define the feature spaces, are a Kansei feature vector and an image feature vector. The ***Neural Network*** method is used to correlate the two feature spaces.

Furthermore, we try to quantify some of our most prominent human perception features, such as the perception of contrast and dominance from an image, and the perception of color composition, as "Pictorial features". By adjusting these multi-dimensional pictorial features, users can modify the pictorial perception of images. The flowchart of our research is shown in **Fig. 1**.

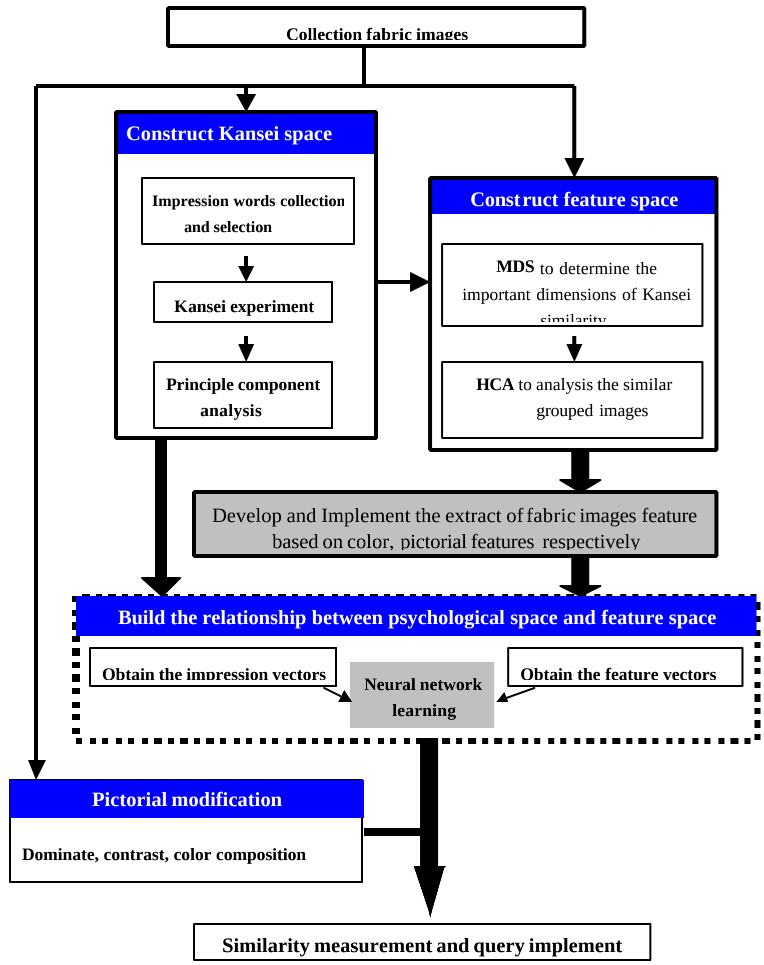


Fig. 1: flowchart of research structure

The outline of the paper is as follows. **Section 1** describes the research motivation and introduces our system and research structure. **Section 2** gives a survey of related works and theories about our research. The Kansei experiments are studied using the SD method and the results of statistic analysis are presented in **Section 3**. In **Section 4**, the details of image processing in extraction of image features based on color and pictorial perception quantification and neural network mechanisms, are expressed. The implementation of our retrieval system is shown in **Section 5**, including the similarity measurement and modification of pictorial features.. In **Section 6**, some conclusions of the thesis and future works will be discussed respectively.

2. Related work

Flexible retrieval and manipulation of image databases has become a relevant and ever increasing problem with applications in video editing, photo-journalism, art, fashion, cataloguing, retailing, interactive CAD, geographic data processing, etc.[5] Until recently, content-based retrieval systems (CBR's) have been used to ask people for key words in order to search image and video databases. One of the earliest CBR systems was ART MUSEUM [6], where retrieval was performed based entirely on edge features. The first commercial content-based image search engine with profound effects on later systems was QBIC [7, 8]. As color representation, this system uses a k-element histogram and average of $(R; G; B)$, $(Y; i; q)$, and $(L; a; b)$ coordinates, whereas for the description of texture, it implements Tamura's feature set [9]. Color, texture, and shape are supported as a set of interactive tools for browsing and searching images in the Photo book system, developed at the MIT Media Lab [10]. In addition to these elementary features, systems such as Visual-seek, Netra, and Virage, support queries based on spatial relationships and color layout[11-13]. Moreover, in the Virage system, the user can select a combination of implemented features by adjusting the weights according to his or her own "perception." This paradigm is also supported in the Retrieval Ware search engine [14]. A different approach to similarity modeling is proposed in the MARS system [15], where the main focus is not in finding the best representation, but rather on the relevant feedback that will dynamically adapt multiple visual features to different applications and different users. Most of the existing systems mentioned above, accomplish this task by expecting the user to assign a set of weights to color, shape, and texture features, thus specifying the way these attributes are going to be combined in the algorithm. However, humans have no general notion of visual similarity, especially in kansei similarity; instead, they possess a functional notion of similarity within a particular domain.

Recently, several methods for an image retrieval system using impression words have been proposed. Although colors, structural design, and objects in an image have great influence on human impression, most of the studies depend only on a color distribution of an image as image characteristics, which are used to estimate impression words[16-20]. Apart from impression words, there are some studies, which use information of the objects in an image[21, 22]. In[18], the developed system named IRIS, the separation of sky/earth/water is done automatically; color and structural characteristics are extracted from the sky/earth/water categories. Then, impression words are estimated automatically.

In our research, we focus on the features of color matching, by the decomposition from the fabric images, which are related to the psychological features of kansei. We perform similarity matching in a human-like manner by the following tasks. (1) Choosing a specific application domain as color matching. (2) Understanding how users judge similarity within color matching domains by way of kansei experiments, and then (3) building a system that will replicate human performance by linking the low-level features of images and the high-level concepts from kansei. In a general setting, however, the low-level features do not have a direct link to the high-level concepts. To narrow down this semantic gap, some off-line and on-line processing is needed[1]. The off-line processing can be achieved by using supervised learning, unsupervised learning, or the combination of the two. Neural nets, genetic algorithms, and clustering are such learning tools [16, 18, 23]. For on-line processing, a powerful and user-friendly intelligent query interface is needed to perform this task. It should allow the user to easily provide his or her evaluation of a current retrieval result to the computer.

3. Construction of the kansei space

The research work of this stage applies the conceptions of Kansei engineering to construct a factor space that is common to fabric images as the mainstay of the kansei model. In this paper, the questionnaire and statistic methods are applied to extract the representative impression words for fabrics. The experiment samples, displayed by computer, are collected by CD-ROM and scanned images from real fabrics. All of the images are normalized to 400x400 pixel pictures, and the impression questionnaire is originally in Chinese.

3.1 Experiment Ⅰ: Extraction of impression words and kansei factor

Before experiment Ⅰ, we made the glossary of 66 adjectives that appropriate for fabrics and asked 100 subjects to pick up the adaptive words for describing the fabrics. Finally, we reserved those impressions that were chosen by more than 35% of the subjects and obtained 40 adjectives. Our questionnaire containing 10 diversified color fabric images collocated with the 40 adjectives of 7 level **Likert scale** glossaries were filled out by 10 subjects with an educational background in design. We analyzed statistically the experiment data by ***Principle component analysis*** (factor analysis), and obtained the 6 factors of the impression words as a result. According to the rotation component matrix of factor analysis, in table 1, we could see the weight of the factor for each adjective and which factor it belonged to. Secondly, we used these factor weights data to process ***Hierarchical Cluster Analysis***, and divided the 40 adjectives into 6 clusters. Comparing the impression words that were closest to the center of each cluster and whose factor weight was higher in factor space, we finally chose 9 adjectives as the kansei features. Due to the indefinite impression of “sport for fabrics”, we ignored the factor 6, which had only one impression word. **Table 1** shows the factor weight of each adjective and which factor it belonged to, as well as, into which cluster it was classified.The adjective labeled * was nearest the cluster center.

Table 1: The result of factor analysis and HCA

Impression words	Wt	Factor	Cluster	Impression words	Wt	Factor	Cluster
leisure	0.93	1	4	beautiful	0.90	2	3
lithe	0.92	1	4	feminine	0.87	2	3
dark	-0.90	1	*1	male	-0.82	2	*2
refreshing	0.90	1	4	neutral	-0.82	2	2
heavy	-0.88	1	1	vivid	0.77	2	*3
bright	0.86	1	4	austere	-0.75	2	2
spring/summer	0.86	1	*4	pretty	0.74	2	3
cool	0.86	1	4	fashion	0.89	3	*6
solemn	-0.85	1	1	high classic	0.87	3	6
ripe	-0.82	1	1	noble	0.84	3	6
soft	0.80	1	4	modern	0.72	3	6
cute	0.80	1	4	fashionable	0.53	3	6
youthful	0.79	1	4	Warm	0.93	4	5
pure	0.78	1	4	individual	-0.68	4	6
old-style	-0.77	1	1	classical	0.59	4	1
Fall/winter	-0.76	1	1	traditional	0.58	4	2
vivacious	0.72	1	3	refined	0.86	5	5
primitive	-0.69	1	1	graceful	0.83	5	*5
tasteful	-0.63	1	1	uncolored	0.69	5	5
Warm keeper	-0.61	1	1	sport	0.88	6	5

3.2 Experiment Ⅱ: Experiment of impression features extraction

In this experiment, 35 subjects were invited to measure their subjective impression of 40 different fabric images using the **semantic differential method (SD)**. All of the subjects were designers, either presently in the fashion design industry, or with some design related training background. Subjects watched each fabric image presented on a display and gave a score based on the 9 adjective pairs in the 7-level SD scale. The selected 9 SD pairs of adjectives (totally 18 adjectives) could be divided into 4 groups, which contained the impressions from factor 1 to factor 5. **Table 2** listed these adjective pairs and their grouping labels, as well as the factors they indicated. We did this experiment in the laboratory, with the luminance set to that of a daytime office.

The purpose of this experiment was to find out the principal visual features influencing the impressions of fabrics. That meant that, by surveying the distribution of experimental fabric images in the factor space, we tended to induce the feature components and rules that affected the kansei feeling of each impression factor. The analysis of the above relationship upon each impression factor was shown respectively as follows:

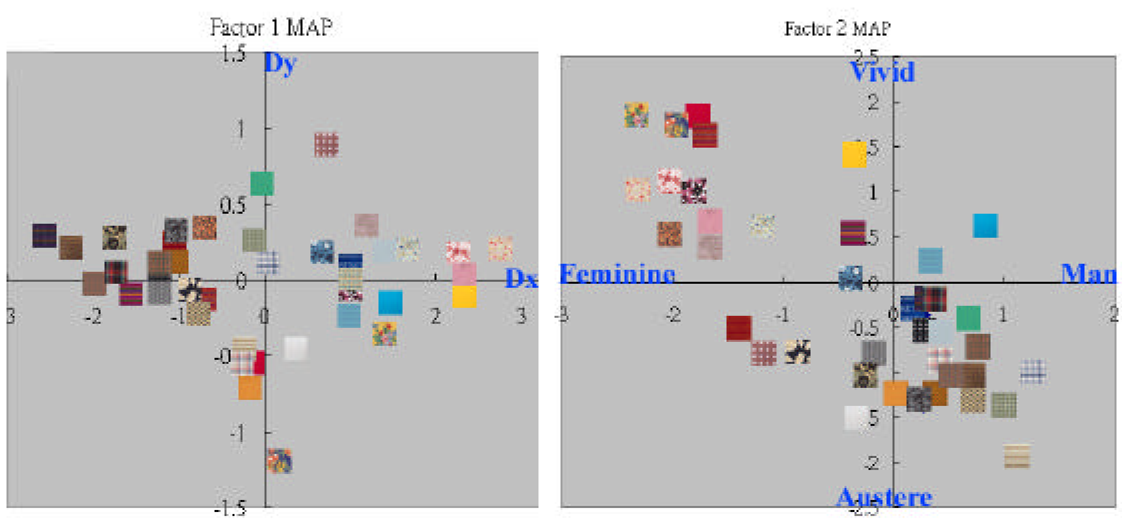
Table 2: The SD pairs of adjectives in experiment Ⅱ.

		G	F
Bright	**Dark**	1	
Lithe	**Heavy**	1	1
Spring/Summer	**Fall/Winter**	1	1
Soft	**Stiff**	1	1
Cute	**Ripe**	1	1
Male	**Feminine**	2	2
Vivid	**Austere**	2	2
Fashion	**Classic**	3	3,4
Graceful	**Rough**	4	5

Factor 1 (bright, lithe, spring/summer, soft and cute): The first step, in the data analysis, was to transfer subjects' impression ratings of factor 1 (bright, lithe, spring/summer, soft and cute) into a 40x40 individual similarity matrix as an input of the MDS analysis. The stress value produced by MDS for 2-dimension was 0.06368. Consequently, it was reasonable that we used 2-dimensional space to inspect the impression similarity of the image samples, as shown in **Fig. 2 (a)**. It seemed that most colors in the positive domain were cool colors, such as blue, white, cyan, pink and bright yellow, as well as a few light, warm colors. On the other hand, most of the warm colors and dark chromatics appeared at the negative end of this axis, and the saturation of colors seemed to decrease. We inferred that the overall brightness of images triggered the crucial effects for this experiment.

Factor 2 (man, vivid): The 2D image map of factor 2 (**Fig. 2 (b)**) was diagrammed upon the impression rating of man/feminine and vivid/austere directly. The more positive position on the vivid/austere axis, the higher the saturation and complex combination of hue distribution in the colors. The crucial impression feature of man/feminine was hue distribution. The colors matching "*Man*" impression included cool colors and dark chromatics, such as brown, ashen etc. Also the regularity and placement of pattern and dominant colors, were less variant, and not as intricate. Consequently, the feminine side showed warmer, more vivid colors, with more intricate and prettier patterns.

Factor 3,4 (fashion, classic): Viewing the distribution of our samples, based on the impression scores of the fashion/classic SD pair (**Fig. 3(a)**), we determined that clear color combinations (such as sample 17, 22) or the purely chromatic pattern, (such as sample 4, 6) would increase the "*fashion*" impression. We also ascertained that those with



(a) **(b)**

Fig. 2: The 2-D map of experimental images for factor 1 and factor 2 . (a) the 2-D map by MDS for factor 1; (b) the 2-D map by impression scale for factor 2.

more complex matching colors (sample 19, 23), and warmer, darker, chromatic colors, would favor the "*classic*" end.

Factor 5 (graceful, rough): No obvious decisive factor was attained for this impression scale by surveying the distribution in **Fig. 3(b)**, which indicated the higher perception in human kansei. However, we determined roughly that the brighter or lighter the color combinations and detailed patterns, the stronger the impression of "*graceful*" would be.

We concluded that there were certainly stable features of color matching that affected our impressions. By the above analysis of our experiments, we defined the feature components of color matching that corresponded to our impression:

(a) The colors of combination

(b) The overall color information

(c) The pictorial complexity

The quantitative image features were established based on the above feature components in the next section.

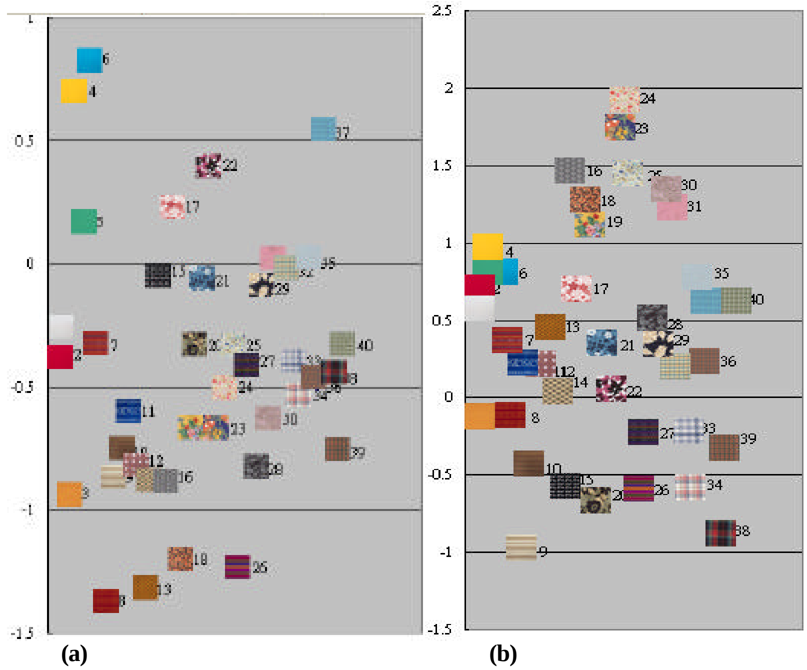


Fig. 3: The 1-D distribution of impression of (a) Factor 3-4; (b) Factor 5.

4. Establishment of image features and neural network mechanism

4.1 Feature extraction based on matching color information

In various query systems, color was to be an important and straightforward attribute. We preferred the **HSV (hue, saturation, value)** color space because **HSV** model which separated the luminance component from chrominance information corresponded closely to the way that human eyes perceived colors[24], as in the human visual system, the first approximation was that each of these components was processed through separate pathways[5]. RGB color space could be converted to HSV color space [25]

We proposed to extract the color features to fit the Kansei feeling as the neural network input nodes. Our extraction system was implemented automatically to process the image samples by the following stages and algorithms below:

Stage 1. Color pre-processing

In this stage, we used the median filter, which was a non-linear filter [25], to eliminate the noise of original images. All the fabric images were normalized to 400 x 400 pixels in advance.

Stage 2. Color histogram

We used the color histogram as the feature of visual components. To obtain the color histogram and to build the indexes

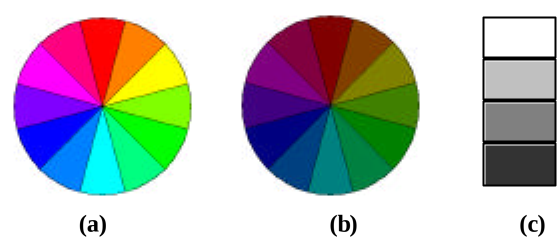


Fig. 4: Inequitable quantized HSV color space: (a) Bright Chromatic, (b) Chromatic, (c) from top to the bottom: White, Dark Gray, Gray and Black, respectively.

into the system, we tried to quantize the HSV model into few colors. However, the quantized colors could not be divided into equal parts in HSV color space. In[26], it was found, experimentally, that bright chromatic pixels tended to be the colors that had value 55% and saturation 20%. By the same way, the color of pixels that had the value between 20% and 50%, and saturation 20% were considered as chromatic pixels. The inequitable quantized HSV color ranges were listed in **Table 3**.

Our proposed method of color indexing implemented quantized HSV color space to distinctively classify a large number of colors into 28-bins of color space. The 28 colors consisted of 12 hues, 2 values and 4 gray-level colors. **Fig. 4** and **Fig. 5** illustrated our inequitable quantized HSV color space and displayed a sample of the procedure mentioned above, respectively.

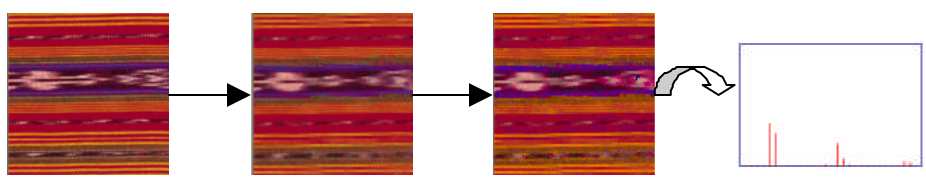
Stage 3. Dominant color extraction

The **k-mean** clustering algorithm[20, 21] had been used to extract the $\boldsymbol{k}$ dominant colors of the fabric images. Considering that there were no rich colors in one fabric image, we defaulted the $\boldsymbol{k}$ =10, and we could obtain the 10 dominant colors and their areas. Then, we eliminated the colors with a small area, which meant the number of the pixels in this area was smaller than $\boldsymbol{T_c}$. We rated the colors by area and obtained the dominant colors $\boldsymbol{N}$ ($\boldsymbol{N} \leqq 10$). Moreover, we defined the purity of domination ($\boldsymbol{D_p}$) by the following steps: (1) Rating the $\boldsymbol{N}$ colors based on the Euclidean distance in RGB space between the $\boldsymbol{C_1}$, which had the max pixels, as ($\boldsymbol{C_1}, \boldsymbol{C_2} \ldots \boldsymbol{C_N}$). (2) From $\boldsymbol{C_1}$ to $\boldsymbol{C_N}$, merging the similar colors that the RGB distance smaller than $\boldsymbol{D_c}$ to obtained the $\boldsymbol{N_f}$ colors. (3) We defined the purity of domination as $\boldsymbol{D_p = N_f / N}$. This value showed the homogeneity of dominant colors approximately. In our case, $\boldsymbol{T_c}$ = 100 and $\boldsymbol{D_c}$ = $(300)^{1/2}$.

Stage 4. Overall color extraction

The overall color information was also an important impression feature. Here, we referred to the following I, I_{RG}, I_{YB} values [16] as color characteristics instead of RGB values.

The three values above represented "intensity" of luminance, "color balance between R(red) and G(green)",and "color balance between Y(yellow) and B(blue)" in a human's visual function. In this stage, we computed the average value of I, I_{RG} and I_{YB}, as well as the mean S_M (saturation) and V_M (value) of one image.



(a) (b) (c) (d)

Fig. 5: The process of generating quantized HSV color space: (a) original image; (b) filtered by median filter; (c) quantized HSV color into 28 bins; (d) HSV histogram.

Stage 5. Pictorial complexity extraction

In this stage, we calculated the coefficient of variation for H, S and V respectively to simulate the pictorial complexity of one image.

4.2 Learning of Neural network

Multi-Layer Perceptrons (MLPs) with the back-propagation learning algorithm, were termed back-propagation networks (BPN)[29-32]. Back-Propagation networks were the most representative and widely used neural networks. BPN was composed of the input layer, the hidden layer and the output layer. Each layer was composed of a different number of neurons.

In this stage, we normalized all of these quantitative image features, calculated from previous steps as our network's inputs. The inputs included the quantized HSV histogram (with 28 bins of colors), mean S,V values, mean I, I_{RG} and I_{YB}, the purity of domination (Dp), and the coefficient of variation of H , S and V. The total number of inputs was 37, and **Table 3** showed the details of input and output nodes. Our network was a multi-layer neural network, which contained the input layer of image features, one hidden layer, and output of impression scores. The NN learning was a supervised model. Usually, we took sigmoid function as an activation model and it was trained by the back propagation algorithm [33].

Input features	**number**	**Output impression values**	**number**
Color histogram	**28**	**Factor 1** 4 pairs of SD adjectives	**5**
Mean S, V	**2**	**Factor 2** 2 pairs of SD adjectives	**2**
Mean I, I_{RG}, I_{YB}	**3**	**Factor 3_4** 1 pairs of SD adjectives	**1**
Dominant purify, Dq	**1**	**Factor 5** 1 pairs of SD adjectives	**1**
Pictorial complexity, CVs, CV_H, CV_V	**3**		
total	**37**		**9**

Table 3:The details of input and output nodes

5. The implementation of a retrieval system

5.1 Similarity measurement

In this part of the system, we performed similarity measurements based on the kansei features and normal color features respectively. The similarity of kansei features was defined according to the distance of impression scores between two images. **Fig. 6** showed an example of querying based on impression features and color features. It was reasonable that the querying results presented were somewhat different.

(a)

(b)

Fig. 6: The example of querying based on (a) impression adjectives, (b) color features. The farthest left is the querying image, followed by four best matches.

5.2 Pictorial modification

In this stage, we performed some mechanisms to change the pictorial vision of images to assist users in matching colors. We quantized the "contrast" and "dominant" two pictorial perceptions in HSV parameters. **Fig. 7** displays the example of pictorial modification.

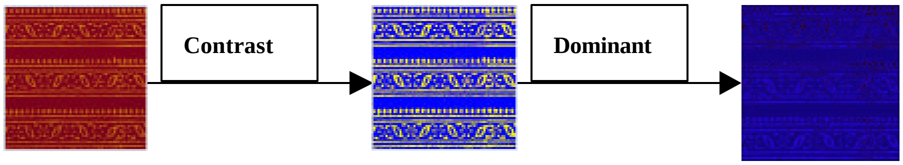


Fig. 7: The example of pictorial modification.

6. Conclusion and future work

Our system could quantize the information of color composition automatically, and users could index the color features of new images and estimate its kansei features by using the trained NN model. If our kansei factor space was common to other domains of images, our kansei retrieval system could be applied more extensively. It's our belief that a good working system of image retrieval should accomplish visual similarity along perceptual dimensions and psychological impressions, or semantic cognition.

The current implementation of our retrieval system focused on the similarity judgment of human's kansei for fabric images. While most of our research of image retrieval was directed at color patterns, we believed that the underlying methodology would also be beneficial for color matching. The effects of color matching impressions from texture and pattern would be interesting, with expandable themes for further research. Besides, people are unique. In today's society, variety is the "spice of life", and opinions vary considerably according to status and life style. Individuality is the essence of our life style, with every man and women having somewhat different impression cognition. The experiments could focus on various groups of people initially and some more objective and obvious kansei features might be extracted in the future.

References

1. Huang, Y.R.a.T.S., Image Retrieval: Current Techniques, Promising Directions, and Open Issues. Visual Communication and Image Representation, 1999. 10: p. 39~62.
2. Nagamachi, M., Kansei engineering as a powerful consumer-oriented technology for product development. Applied Ergonomics, 2002. 33(3): p. 289-294.
3. Ishihara, S.I., Keiko; Nagamachi.etc, An automatic builder for a Kansei Engineering expert system using self-organizing neural networks. International Journal of Industrial Ergonomics, 1995. 15(1): p. 13-24.
4. Nakada, K., Kansei engineering research on the design of construction machinery. International Journal of Industrial Ergonomics, 1997. 19(2): p. 129-146.
5. Mojsilovic, A.K., J.; Jianying Hu; Safranek, R.J.; Ganapathy, S.K., Matching and Retrieval Based on the Vocabulary and Grammar of Color Patterns. Image Processing, IEEE Transactions on, 2000. 9(1): p. 38 -54.
6. Katzo, K.H.a.T., Query by visual example, content based image retrieval. in Advances in Database Technology,580, A. Pirotte, C. Delobel, and G. Gottlob, Eds, 1992.

7. Niblack, W., The QBIC project: Quering images by content using color, texture and shape. SPIE Storage and Retrieval for Image and Video Data Bases, 1994: p. 172-187.
8. C. Faloutsos, M.F., W. Niblack, D. Petkovic,W. Equitz, and R. Barber, Efficient and Effective Querying by Image Content. Technical Report, IBM Research Report, 1993.
9. H. Tamura, S.M., and T. Yamawaki, Textural features corresponding to visual perception. IEEE Trans. Syst., Man, Cybern, 1982. 8: p. 460-473.
10. A. Pentland, R.W.P., and S. Sclaroff, Photobook: Content-based manipulation of image databases. Int. J. Comput. Vis, 1996. 18: p. 233-254.
11. Jain, A.G.a.R., Visual information retrieval. Commun. ACM, 1997. 40: p. 70~79.
12. Manjunath, W.Y.M.a.B.S., Netra: A toolbox for navigating large image databases. in Proc. IEEE Int. Conf. Image Processing, 1997: p. 568~571.
13. Chang, J.R.S.a.S., Visualseek: A fully automated content-based query system. in Proc. ACM Multimedia?6, 1996: p. 87-98.
14. Dowe, J., Content based retrieval in multimedia imaging. in Proc. SPIE .Conf. Storage and Retrieval for Image and Video Databases, 1993.
15. Y. Rui, T.S.H., and S. Mehrotrain, Content-based image retrieval with relevance feed-back in Mars. Proc. IEEE Conf. Image Processing, 1997: p. 815~818.
16. Kaori YOSHIDA, T.K.a.T.Y., Image Retrieval System using Impression Words. Proc. of 1998 IEEE Int'l Conf. on System Man and Cybernetics, 1998: p. 2780-2784.
17. T. Hayashi, M.H., Image query by impression words--the IQI system. IEEE Trans. Consumer Electron, 1998. **44**: p. 347~352.
18. Kazuhiro Kuroda, M.H., An image retrieval system by impression words and specific object names-IRIS. Neurocomputing, 2002. **43**: p. 259~276.
19. Takagi, H., Noda, T. and Cho, S.-B., The psychological space of common media impressions held in a media database retrieval system. Systems, Man, and Cybernetics, 1999. IEEE SMC '99 Conference Proceedings, 1999. **6**: p. 263-268.
20. Fukuda, M.K., M. and Shibata, Y, Perceptional link method based on dynamic hypermedia system for design image database system. System Sciences, Proceedings of the Twenty-Ninth Hawaii International Conference on, 1996. **2**: p. 291 -298.
21. M. Mukunoki, M.M., K. Ikeda, A retrieval method of outdoor scenes using object sketch and an automatic index generation method. Trans. IEICE J79-D-II(6), 1996: p. 1025~1033.
22. H. Nishiyama, Y.M., An image retrieval system considering image composition. Inform. Process. Soc. Japan 37(1), 1996: p. 101-109.
23. Manjunath, W.Y.M.a.B.S., Texture features and learning similarity. in Proc. IEEE Conf. on ComputerVision and Pattern Recognition, 1996: p. 425~430.
24. Xie, X.Y.M., Hand image segmentation using color and RCE neural network. Computational Intelligence in Robotics and AutomationIEEE International Symposium on, 2001. **34**: p. 235-250.

25.Castleman, K.R., Digital Image Processing. Prentice-Hall,Englewood, 1996.

26.D. Androutsos, K.N.P.a.A.N.V., A novel vector-based approach to color image retrieval using a vector angular-based distance measure. Computer Vision and Image Understanding, 1999. **75**: p. 46-58.

27.Hachimura, K., Retrieval of paintings using principal color information. Pattern Recognition, 1996., Proceedings of the 13th International Conference on, 1996. **3**: p. 130 -134.

28.Chou, M.-C.S.C.-H., A modified version of the K-means algorithm with a distance based on cluster symmetry. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 2001. **23**(6): p. 674 -680.

29.Kung., S.Y., Digital neural networks. 1993, Englewood Cliffs, N.J: Prentice Hall.

30.Orille, A.L.S., G. M. A, Application of neural networks for direct torque control. Computers & Industrial Engineering, 1999. **37**(1-2): p. 391-394.

31.Yun, L.H., Alexander, Artificial evolution of neural networks and its application to feedback control. Artificial Intelligence in Engineering, 1996. **10**(2): p. 143-152.

32.Huang, S.-W.H.a.H.C., A neural network based approach for product form design. Design Studies, 2002. **23**: p. 67~84

33. N. N. R. Ranga Suri , Dipti Deodhare, Parallel Levenberg-Marquardt-based Neural Network Training on Linux Clusters -A Case Study, 1995.