Developing a Document Creating System for Affective Design: A Case Study in Card Design

Qianru QIU and Kengo OMURA

Fuji Xerox Co. Ltd., 6-1 Minatomirai, Nishi-ku, Yokohama-shi, Kanagawa 220-8668, Japan

Abstract: In recent years, affective design is found to have great application values in document design that help reduce the load of design works and improve the satisfaction of consumers. However, most research results of affective design are merely used as design guidebooks. A mass of design features make ordinary people confused and incapable to achieve a high quality design scheme. In this paper, an approach is proposed to establish an affective design system that can create a design scheme automatically by a feature combination engine. As a branch of document design, card design is acted as first trial application. In this study, a kansei evaluation experiment was executed and the experiment data was analyzed by factor analysis and quantification theory type I. We also built an ontology-based domain model and established an automatic design system for name card. Moreover, the quality of system output was verified by evaluation experiments.

Keywords: *Affective design, Card design, Feature combination*

1. INTRODUCTION

1.1 Background

Documents play an important role in people's daily activities. Reflecting the timeline of document design [1], there has been a growing tendency of digitization and integration. Document design is the field concerned with integrating color, typography, text, graphics, etc. in the creation of a document. The knowledge about creating documents that can meet the preferences of viewers is needed to be well developed. As a consumer-oriented technology for product development, Kansei/Affective Engineering (KE) [2] has been verified to be powerful in many design fields, such as textile product design [3], and bridge landscape design [4]. While affective design knowledge as a guidebook is still difficult for non-designers to realize an efficient use, and it is well-known that design work by professional designers cost a lot. Therefore, to reduce the cost in design works, an automatic design system which can create a high quality design scheme is urgently needed. The workers who have less design knowledge can also achieve high quality documents to fit customers' demands well and even make batch printing convenient. Therefore, it is conceivable that the document creating system has a high commercial value.

1.2 Related work

The current study in KE is mature in the quantitative analysis phase of creating kansei database. Most of the

affective knowledge is well applied in the aspect of information retrieval and classification. However, showing the pre-existing product drawing as a reference for design is insufficient. The demand of creating new products by affective design is rising. The poster creating support system in [5] and [6] was proposed using genetic operations and fuzzy inference to create layouts, while the outcome was with less aesthetic feeling. Referring to the works of font creating system in [7] and landscape picture creating system in [8], these studies accumulated some data and experience on some independent objects.

The work presented in [9] is an early attempt to combine KE and ontology technology, and it verified that ontology has a good performance on annotating and archiving photos database. Considering that the statistical data in kansei database is lack of an extensible structure, an ontology-based feature model was proposed to realize formalizing, sharing and reusing of affective information. As a preliminary work, the study in [10] proposed a general ontology model for kansei database which distinguished design features into independent-dependent concept clusters and chief-minor concept clusters.

Based on the ontology-based feature modeling method, the work in this paper proposes a complete procedure for establishing an automatic creating system for affective design. It is an in-depth and detailed research for document creating system, especially for card design. The combination method is extended and aesthetic knowledge is blended to improve design quality and system practicality. The quality of outcome has been

verified compared to man-made design work. In addition, the effect of golden ratio in card design is also evaluated.

2. RESEARCH FRAMEWORK

In our research, we proposed an approach of developing an automatic document creating system for affective design. The procedure shown in Figure 1 is divided into 2 processes, as Affective Data Acquisition and Establishment of Design System.

The Affective Data Acquisition part is based on the procedure of Kansei Engineering Type II. It aims to collect affective data including kansei words, design features in a certain field, and the associated values between design features and kansei words. The basic issue is to confirm the target field and then extract main design features and relevant kansei words. It would be better if done with the cooperation of relevant experts. In the evaluation experiment, SD method is used to measure the humans' impressions about design object and some statistical methods are used to do data analysis. Here, factor analysis

classifies kansei words into different semantic clusters, and the quantification theory type I is used to clarify the associated values between design features and kansei words.

In the Establishment of Design System part, the domain ontology model is built based on the method in [10]. Since the outcome got from pure combination of design elements can't obtain high design quality, a variety of combinational rules based on some professional design knowledge should be made and integrated into the design engine. Here, aesthetic knowledge should be quantified and flexibly used. Even relevant design knowledge can be reused in other design fields. The user interface is built to show the design candidates made by the design engine and achieve the interaction between design system and users. Moreover, some evaluation reviews are executed to ensure the affective efficiency of automatic design work.

This study is focused on the field of card design as our first trial research target and Japanese name card is selected as target object. In our work, we acquired affective design data and established an automatic design system for card design. This system architecture is extensible for other document design.

Figure 1: Procedure of Developing A Document Creating System for Affective Design

3. AFFECTIVE DATA ACQUISITION

3.1 Kansei evaluation experiment

As evaluation samples, 288 Japanese name cards were made referring to experts' advice and these samples were divided into 8 groups by gender, color mode, horizontal and vertical version. 30 kansei words which are shown in Table 1 were extracted to express the impressions on design images.

Table 1: Vocabulary of KANSEI Words

Japanese	English	Japanese	English
プリティ	Pretty	ポップ	Pop
カジュアル	Casual	ロマンチック	Romantic
ダイナミック	Dynamic	若々しい	Youthful
ナチュラル	Natural	知的な	Intellectual
エレガント	Elegant	落ち着いた	Calm
ゴージャス	Gorgeous	上品な	Graceful
ワイルド	Wild	個性的な	Special
クラシック	Classic	重厚な	Profound
フォーマル	Formal	遊び心のある	Vigorous
ダンディ	Dandy	やわらかい	Soft
シック	Chic	目立つ	Conspicuous
フレッシュ	Fresh	読みやすい	Readable
クリア	Clear	記憶に残る	Impressive
クール	Cool	ビジネス向きの	Commercial
モダン	Modern	好き	Like

The investigation was executed by online questionnaire survey entrusted to a marketing research company, Marcomill. It was conducted for 702 Japanese office workers which were composed of 348 female and 354 male workers. The age of these respondents had nearly an average distribution in twenties, thirties, forties and fifties.

3.2 Factor analysis results

Factor analysis is used to recognize semantic clusters and varimax rotation has the effect of differentiating the original variables by extracted factors. The factor loadings obtained by varimax rotation are shown in Table 2. In our case study of card design, 5 factors are selected as axial factors, “Wild”, “Pretty”, “Natural”, “Dandy” and “Elegant”. Most factor loadings are more than 0.4, which represents that the result is reliable. Also, the rest of factor loadings are close to 0.4, and these adjectives are classified into the nearest clusters. The table below also shows the Eigen value,

Table 2: Results of Factor Analysis by Varimax Rotation

Kansei words		F1	F2	F3	F4	F5
Wild	Impressive	1.0132	0.1800	0.3250	-0.1392	0.1490
	Dynamic	0.9969	-0.1111	0.0232	0.1298	-0.0829
	Wild	0.9884	-0.2419	0.0147	0.2071	-0.0277
	Conspicuous	0.9880	0.1370	0.1371	-0.0606	0.0821
	Special	0.7407	0.2666	-0.1723	0.0348	0.1613
	Vigorous	0.5591	0.4982	-0.1649	0.0166	0.0214
Pretty	Fresh	0.1174	0.8972	0.0802	0.3773	-0.1132
	Soft	-0.0998	0.8968	0.1573	-0.1705	0.2118
	Pretty	-0.0651	0.8835	0.0289	-0.1815	0.1758
	Youthful	0.3808	0.7806	0.0387	0.0338	-0.0458
	Casual	0.3767	0.7161	0.0136	0.0039	-0.0949
	Pop	0.4521	0.6348	-0.0841	-0.0055	-0.0967
Natural	Readable	0.2802	-0.0084	1.1355	-0.2029	-0.0989
	Commercial	-0.1779	-0.2405	0.7375	0.0859	-0.2472
	Like	0.0318	0.3960	0.6968	0.1007	0.1830
	Natural	-0.3115	0.5102	0.5659	0.1948	-0.0364
	Calm	-0.4003	-0.1600	0.4346	0.1962	0.0975
	Formal	-0.3626	-0.2820	0.3749	0.2495	-0.0101
Dandy	Classic	-0.3152	-0.2976	0.2973	0.2851	0.1103
	Cool	-0.1369	-0.0249	-0.0791	0.9026	-0.0155
	Clear	-0.1805	0.4457	0.2868	0.7056	-0.1758
	Modern	0.2021	0.2018	-0.3095	0.6662	0.3940
	Dandy	0.2996	-0.3397	0.0601	0.6390	0.0659
	Chic	-0.2793	-0.2866	0.0925	0.4973	0.1983
Elegant	Intellectual	-0.2605	-0.0904	0.3589	0.3867	0.1676
	Elegant	-0.1845	0.1392	0.0411	0.0134	0.8425
	Gorgeous	0.2161	-0.0175	-0.0994	0.1463	0.8286
	Romantic	-0.1488	0.6189	-0.0339	-0.0890	0.6291
	Graceful	-0.3415	-0.0670	0.3428	0.1584	0.4171
	Profound	0.3121	-0.3538	0.2654	0.3473	0.3635
Eigen value		13.8609	5.5031	3.0209	1.6243	0.9099
Contribution ratio (%)		46.20	18.34	10.07	5.41	3.03
Accumulated contribution ratio (%)		46.20	64.55	74.62	80.03	83.06

contribution ratio and accumulated contribution ratio that provide a deep understanding of these 5 semantic clusters.

3.3 Analysis results of quantification theory I

For the analysis of quantification theory type I, the first issue is to extract design features and create the items/categories table. Considering that the samples are divided into color mode and gray mode, and half of the samples have a photo while half do not, the design features are divided into 3 parts: entire part, color part and photo part. Entire part contains general features, such as background, layout, etc. Since the person's name and company's name are proved to have a significant impact on the perceived impression of name card, the relevant design features of these 2 elements are also included in entire part. Color part contains the properties of color. Here, hue and tone are fixed to locate specific color. Photo part includes the properties of photo, such as shape, size, etc.

From the overall perspective, the multiple correlation coefficients of kansei words are shown in Table 3. In the entire part, all coefficients are more than 0.8 which indicates that the relationship between items/categories and kansei words is highly reliable. The analyzed data in

Table 3: Multiple Correlation Coefficients

Kansei words	Multiple correlation coefficient		
	Entire part	Color part	Photo part
Pretty	0.9804	0.8304	0.8467
Casual	0.9835	0.8257	0.7245
Dynamic	0.9841	0.5956	0.6493
Natural	0.9572	0.6061	0.6843
Elegant	0.9736	0.6416	0.7086
Gorgeous	0.9688	0.6690	0.6426
Wild	0.9789	0.6001	0.6402
Classic	0.9762	0.7341	0.6399
Formal	0.9763	0.7198	0.6135
Dandy	0.9347	0.7877	0.7808
Chic	0.9730	0.7814	0.6219
Fresh	0.9392	0.8532	0.7393
Clear	0.8955	0.6049	0.5105
Cool	0.9595	0.7536	0.4607
Modern	0.9500	0.6097	0.6152
Pop	0.9851	0.8191	0.6408
Romantic	0.9777	0.7635	0.8562
Youthful	0.9745	0.8607	0.7103
Intellectual	0.9765	0.6340	0.5795
Calm	0.9811	0.6583	0.6243
Graceful	0.9754	0.6240	0.6534
Special	0.9757	0.6644	0.6150
Profound	0.9231	0.7940	0.7059
Vigorous	0.9784	0.7507	0.6458
Soft	0.9751	0.8518	0.8610
Conspicuous	0.9769	0.6040	0.6090
Readable	0.9426	0.4196	0.6097
Impressive	0.9676	0.5914	0.5805
Commercial	0.9747	0.6951	0.6445
Like	0.9207	0.4912	0.6681

color part and photo part is used as auxiliary information for feature combination.

For one kansei word, the partial correlation coefficient of an item shows the strength of influence on affective expression. In addition, the value of score represents the quantified relationship between category and kansei word. Figure 2 shows partial results of entire part design features for wild analyzed by quantification theory type I.

4. ESTABLISHMENT OF DESIGN SYSTEMN

4.1 Feature modeling

The concept hierarchy of design object can be built based on the general ontology model which is proposed in [10]. In the general ontology model, there are 3 design concepts: DesignObject, DesignElement and DesignItem. DesignObject represents the product object in the design

Figure 2: Partial Results of Quantification Theory Type I for Name Card Regarding “Wild”

Developing a Document Creating System for Affective Design: A Case Study in Card Design

Figure 3: Ontology Class Hierarchy for DesignObject

field as the classes shown in Figure 3. DesignElement represents the physical components contained in product object, and DesignItem represents the properties in design elements. Other concepts are all inherited from these 3 basic concepts. Furthermore, an object with a specified kansei is denominated in the structure of “Kansei+Object”, e.g. PrettyObject, WildObject. It is same that the structures of “Kansei+Element” and “Kansei+Item” are used for design element and design item.

For card design, the class model and object property model are shown in Figures 4 and 5. CardDesign is defined as DesignObject, and Entirety which includes properties such as ColorMode, PaperPattern, Background, etc, is defined as IndependentElement. Name and Company are defined as ChiefElement, while others are defined as MinorElement.

After feature modeling, design properties are restricted to complete the ontology knowledge base.

Figure 4: Class Model of Card Design

Figure 5: Object Property Model of Card Design

4.2 Feature combination

A feature combination strategy is necessary to integrate a complete design scheme. In the ontology knowledge base, each kansei word is linked with several values of design items. All these values together determine the result of design scheme.

For example, the value set S for design object which is corresponding to pretty is shown as follow.

$$S_{\text{Pretty}} := \{\cup a_1.\text{value}, \cup a_2.\text{value}, \cup a_3.\text{value}\}$$

where

$$a_1 \subseteq (\text{PrettyItem} \wedge \text{IndependentItem})$$

$$a_2 \subseteq (\text{PrettyItem} \wedge \text{ChiefItem})$$

$$a_3 \subseteq (\text{PrettyItem} \wedge \text{MinorItem})$$

A feature selection and combination strategy works in a feature combination engine. Since the tree structure of feature model represents the logical structure of design concept, it is apparent that the design feature is composed of a design element and a design item. The process of feature selection is to traverse the path of concepts to select associated characteristic value at the end of the tree model. The complete path is as DesignObject → DesignElement → DesignItem → Value.

Depth First Strategy and Breadth First Strategy are widely used as top-to-down approach of graphs and trees. Figure 6 shows the general view of these 2 strategies applied for affective design. The abbreviation is KDO for Kansei Design Object, KDE for Kansei Design Element, KDI for Kansei Design Item and V for Value.

Figure 6: General View of DFS and BFS

Depth First Strategy (DFS)

DFS starts at the root node KDO, and follows one of the branches as deep as possible until it reaches a leaf node that has no child node. Here, the first complete route ends with node “V” as $R_1(KDO, KDE_1, KDI_{11}, V_{11})$. Then it turns back to the layer KDE and goes along a second direction. Repeat the process until all items are being accessed and then go back to the layer KDO. The process is stopped when all nodes are accessed. The pseudo-code is shown in Algorithm 1.

Algorithm 1: Feature Selection and Combination of Depth First Strategy

Require: Kansei K

```

1: Initialize Object  $KDO$ , Feature  $R$ 
2: foreach  $KDE$  in  $KDO.KDE$  do
3:   foreach  $KDI$  in  $KDE.KDI$  do
4:     if  $KDE$  is in  $IndependentElement$  and  $KDI$  is in
5:        $IndependentItem$  then
6:          $R.Independent.add(KDO, KDE, KDI,$ 
7:            $KDI.V)$ 
8:       end if
9:       if  $KDE$  is in  $ChiefElement$  and  $KDI$  is in
10:         $ChiefItem$  then
11:           $R.Chief.add(KDO, KDE, KDI, KDI.V)$ 
12:        else
13:           $R.Minor.add(KDO, KDE, KDI, KDI.V)$ 
14:        end if
15:      end foreach
16:    end foreach
17:    while  $!R.Independent.empty$  do
18:      if has conflict then
19:        adjust  $R.Independent.V$ 
20:      end if
21:      DrawObject( $R.Independent.KDE, R.Independent.KDI,$ 
22:         $R.Independent.V$ )
23:    end while
24:    while  $!R.Chief.empty$  do
25:      if has conflict then
26:        adjust  $R.Chief.V$ 
27:      end if
28:      DrawObject( $R.Chief.KDE, R.Chief.KDI, R.Chief.V$ )
29:    end while
30:    while  $!R.Minor.empty$  do
31:      if has conflict then
32:        adjust  $R.Minor.V$ 
33:      end if
34:      DrawObject( $R.Minor.KDE, R.Minor.KDI, R.Minor.V$ )
35:    end while

```

Breadth First Strategy (BFS)

BFS also starts at the root node KDO, and accesses its child nodes as far as possible. Add all these child nodes to a stack. Then pull out a node and go ahead to access its child node. Here, the first complete route also ends with node “V”. The order of routes is $R_m(KDO, KDE_k, KDI_{km}, V_{km}), R_{m-1}(KDO, KDE_{k,m-1}, KDI_{k,m-1}, V_{k-1,1}), \dots, R_1(KDO, KDE_k, KDI_{k1}, V_{k1})$. It aims to obtain a diverse way for feature selection and combination. The pseudo-code is shown in Algorithm 2.

4.3 Combined with design knowledge

Design knowledge refers to design rules and attractions which aim to ensure the quality of the design scheme.

The rules are a series of design parameters formulated by professional designers which acts as basic standards for automatic design. For instance, margin should be larger than 5 millimeters, font size should be larger than 5 points, and so on.

Algorithm 2: Feature Selection and Combination of Breadth First Strategy

Require: Kansei K

```

1: Initialize Object  $KDO$ , Feature  $R$ 
2: Define<List>  $KDEStack$ 
3: Define<List>  $KDIStack$ 
4: foreach  $KDE$  in  $KDO.KDE$  do
5:    $KDEStack.push(KDE)$ 
6: end foreach
7: foreach vertex  $KDE$  in  $KDEStack$  do
8:   foreach  $KDI$  in  $KDE.KDI$  do
9:      $KDIStack.push(KDI)$ 
10:   end foreach
11:   foreach vertex  $KDI$  in  $KDE.KDIStack$  do
12:     if  $KDE$  is in  $IndependentElement$  and  $KDI$  is in
13:        $IndependentItem$  then
14:        $R.Independent.add(KDO, KDE, KDI,$ 
15:          $KDI.V)$ 
16:     end if
17:     if  $KDE$  is in  $ChiefElement$  and  $KDI$  is in
18:        $ChiefItem$  then
19:        $R.Chief.add(KDO, KDE, KDI, KDI.V)$ 
20:     else
21:        $R.Minor.add(KDO, KDE, KDI, KDI.V)$ 
22:     end if
23:   end while
24: end while
25: while  $!R.Independent.empty$  do
26:   if has conflict then
27:     adjust  $R.Independent.V$ 
28:   end if
29:   DrawObject( $R.Independent.KDE, R.Independent.KDI,$ 
30:      $R.Independent.V$ )
31: end while
32: while  $!R.Chief.empty$  do
33:   if has conflict then
34:     adjust  $R.Chief.V$ 
35:   end if
36:   DrawObject( $R.Chief.KDE, R.Chief.KDI, R.Chief.V$ )
37: end while
38: while  $!R.Minor.empty$  do
39:   if has conflict then
40:     adjust  $R.Minor.V$ 
41:   end if
42:   DrawObject( $R.Minor.KDE, R.Minor.KDI, R.Minor.V$ )
43: end while

```

Figure 7: Grid Setting by Golden Ratio for Card Design

The attractions refer to aesthetic knowledge that can cause a perceptual experience of beauty in design works. It's worth noting that the golden ratio plays a significant role in graphic design. In our work, golden ratio is used to optimize and adjust the layout of text contents, the jump rate of font size, and even the width of margin. Figure 7 shows the grid setting for card design. Since the system is established as a web service, the physical paper size is converted into pixel. The text contents are located in their appropriate golden areas. The effect of optimization is verified by experiments in next section.

4.4 System Establishment and verification

The architecture of design system is divided into 3 layers shown in Figure 8.

Data layer mainly includes kansei data sets analyzed by statistical methods and design knowledge. Control layer works as the design engine on the inter-coordination between feature combination category and design rules. In the interaction layer, users can input kansei words and their own contents. The output is shown as a design candidate. The output for 2 kansei words with specified mixing rate is also available. In addition, users can make changes of contents' size, location, and angle of slope by themselves. The framework of golden ratio is used for easy self-judgment which is shown in Figure 9.

To verify the quality of system output, 2 evaluation experiments were executed. From 5 semantic clusters, 5 tastes are chosen including pretty, natural, elegant, wild and dandy. 20 Japanese office workers participated in these experiments. All these participants are with less aesthetic experience.

Figure 8: Architecture of Automatic Design System

Figure 9: Output Screen of Automatic Design System

In experiment 1, the evaluation objects included 3 parts for each selected taste. Part1 contained the top4 samples made by human beings according to the scores in kansei evaluation experiment. Part2 contained the top4 design candidates without the adjustment of golden ratio, and part3 contained the top4 candidates with the adjustment of golden ratio. In the design system, diverse candidates are integrated for each taste and their priorities are based on the category scores in the results of quantification theory type I. These name cards were shown together in a random order and participants were asked to rank these cards from 1 to 12 in order according to impression intensity. As rank1 has 12 points, rank2 has 11 points, and so on. Then we got the scores of 12 cards which describe the degree of taste.

Friedman test is used to detect differences in treatment across samples, candidates with golden ratio and candidates without golden ratio. The results in Figure 10 represents

Figure 10: Results of Evaluation Experiment 1

that pretty, natural, wild, dandy get a good performance which shows that the candidates integrated by system can have the same strength of taste as samples made by human beings. Especially for natural, the system outcome can have much stronger impression than samples. However, for elegant, the design candidates should be improved in future work.

The difference made by golden ratio is not evident in experiment 1. To make further explorations of golden ratio, the next experiment focused on the candidates made by design system.

The experiment 2 aimed to examine the effect of golden ratio on the design quality of name card. For 5 specified tastes, each taste had 2 matched candidates, and 10 pairs of design candidates were chosen as the evaluation objects. Each pair contained 2 candidates, one was adjusted with golden ratio and the other one was not. During the experiment, participants were asked to choose the one having stronger high-grade sensation in each pair.

Here, Wilcoxon signed-rank test is used to measure the difference among candidate pairs. It is found that the candidates with golden ratio have stronger high-grade sensation. The p value by Wilcoxon signed-rank test is less than 0.01 which means that the difference is significant. Furthermore, as the preference distribution shown in Figure 11, golden ratio has an obvious superiority in the candidates of dandy and elegant which have a close meaning with high-grade. The p values in dandy and elegant are much less than 0.01. However, it does not have a significant difference for the other 3 tastes, pretty, natural, and wild. The performance is same as the results of kansei evaluation experiment on cuboids with a square section in research [11], that golden ratio only has a good performance for modernistic tastes, as elegant, modern, and high-grade. Since wild has an opposite meaning of

Figure 11: Preference Distribution of Design Candidates for High-grade Sensation in Experiment 2

high-grade in kansei space, it is perceptible that golden ratio has a bad performance in the candidates of wild. Considering that name card is widely used in business scenes and the target users almost have not good aesthetic intuition, the delicate difference caused by golden ratio is ambiguous in the candidates of pretty and natural. In general, golden ratio as aesthetic knowledge can improve high-grade sensation in card design.

5. CONCLUSIONS

Recently, document design is facing a technical and dynamic challenge and it will no longer just rely on professional designers. KE provides a powerful support by acquiring affective database. In this research, a procedure for developing a document creating system for affective design is proposed and it is applied to the study of card design. The data of kansei evaluation experiment has been analyzed by factor analysis and quantification theory type I. Based on the ontology feature modeling, the combination categories work well and some conflicts between design contents has been avoided. On the user interface of design system, users can obtain a complete design scheme which is corresponding to their affective demands. The system output is verified to have an equivalent effectiveness to that of man-made work. And golden ratio has been proved to have superiority for high-grade sensation.

Aesthetic feeling has been considered as a key point in a document creating system. In our future work, more aesthetic knowledge will be quantified and loaded into the design system. Also, the design object will be expanding to other document design fields.

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Qianru QIU

Qianru Qiu is a research assistant of Research & Technology Group, Fuji Xerox in Yokohama, Japan. She received her Master degrees in software engineering from Shanghai Jiao Tong University, China in 2014. She joined FX Visiting Fellowship Program when she was a student in 2012 and started the research of affective design. She is now engaging in Kansei evaluation of document design and establishment of automatic design system.

Kengo OMURA (Member)

Kengo Omura is a cognitive psychologist and a senior researcher at the communication design office of Fuji Xerox in Yokohama, Japan. He received Master of Arts from Keio University in 1984. His research interests include psychology of design and Kansei/affective engineering for document design.