Kansei Design Method for Building Exterior by Inverse Problem Approach of Decomposed Fuzzy Model

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Abstract

A new Kansei design method by using decomposed fuzzy model and its inverse problem solution is proposed. Building exterior design is reported as an application of the method. Input variables of the model are building exterior attributes, i.e. color of the exterior, window type, and wall material type. Output variables of the model are five major factors of Kansei adjective pairs obtained by SD technique. The model consists of sub-models corresponding to each output variable, and the input variables are common among these sub-models. Simplified fuzzy inference is used for each input variable in order to represent monotonicity of Kansei. The output variables of fuzzy inference are hierarchically combined two by two by combination unit, which is a nonlinear function based on Kolmogolov-Gabor polynomial. Inverse problem of each sub-model is solved by firstly calculating noninferior solution set of combination unit hierarchically, and secondly calculating inverse image of fuzzy inference. By taking intersection on solution sets of all sub-models for each input variable, we obtain the solution set of Kansei design problem as a possible change of building exterior attributes.

Key Words: Kansei design, Inverse problem, Fuzzy model

1 Introduction

In the recent development of factory automation and information technology, production of industrial goods is being changed from mass-production-small-variety to small-production-wide-variety. Industrial design is going to be ready to design a product to satisfy each customer's request separately. However, it cannot be said that customer's impression to industrial products have been investigated well, so there remain many problems to be solved in this field.

From a part of trial to solve these problems, "Kansei" is a key word that attracts notice. Kansei is a Japanese word that means human feeling, for example in industrial design, about products. Among many proposals to measure the Kansei, semantic differential(SD) technique is one of the most traditional method [1]. In this method, Kansei is firstly measured by grades between many pair of two opposite meaning adjectives, and factor analysis is applied to extract axes to represent the Kansei.

In this paper, we propose a new model of customer's Kansei evaluation and its inverse problem solution, and we apply them to a design of building exterior. The input of the model are attributes of design object, and the output are factors that represent human Kansei. From many input and output pairs of human reaction measured by enquiry, parameters of the model are tuned to approximate the human reaction. By applying inverse problem solution to this model, we can obtain variation of design object attributes to satisfy the customer's request represented by the change on the factors of human Kansei.

The model is decomposed into sub-models corresponding to each output variable, and the input is common among these sub-models. Each sub-model consists two basic units, fuzzy inference unit and combination unit. In fuzzy inference unit, simplified fuzzy inference is applied for each input variable in order to represent nonmonotonicity of Kansei. The output variables of fuzzy inference are hierarchically combined two by two by combination unit. Combination unit is a nonlinear function based on Kolmogolov-Gabor polynomial.

Inverse problem of each sub-model is solved as follows. Firstly, calculate noninferior solution set of combination unit from output to input hierarchically. Then we obtain solution set on output of fuzzy inference. Secondly, calculate inverse image of the solution set for each fuzzy inference. Then we have solution set on input variable for each sub-model. By taking intersection on solution sets of all sub-models for each input variable, we obtain the solution set of Kansei design problem as a possible change of building attributes.

2 Measurement of Kansei

2.1 CG image

The object where human Kansei is measured is building exterior. As the object, CG(computer graphics) images of building exterior are used. Attributes of CG image are color factors, wall material, and window type. The color is represented by Munsell color notation system in which the factors are hue, value, and chroma. Wall material takes three types, tile, sprayed tile, and steal panel. We have two window types, separate type and continuous type. Figure1 shows an example of CG image.

2.2 SD technique

To measure Kansei of human, SD(Semantic Differential) technique is used. Factor analysis to obtain orthogonal solution is applied with conditions principal analysis method to determine communality, rotation by varimax criterion. The number of factors is determined by looking cumulative contribution rate.

2.3 Clustering

To adapt individuality of human, we apply clustering method to human reaction. By summing up factor scores with respect to all CG images for each person, we obtain factor score vector for each person. Clustering is applied to these vector, and we have some groups of person. As the clustering method, we have employed the fusion technique. Group-average with Euclidean distance is used as a similarity measure.

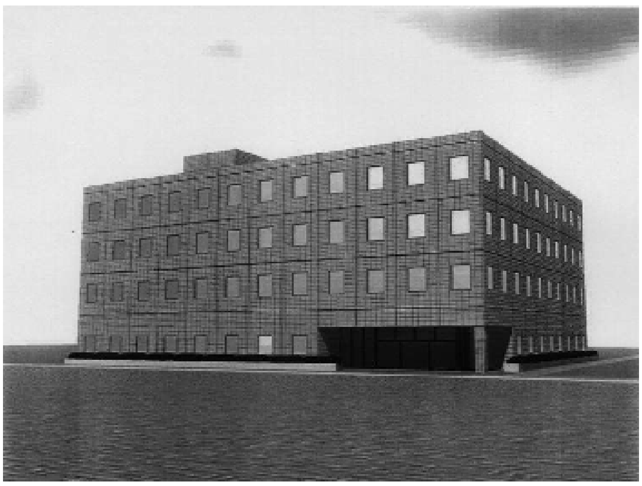

Figure 1: CG image of building exterior

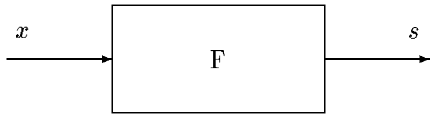

Figure 2: Symbol of nonlinear mapping by fuzzy inference

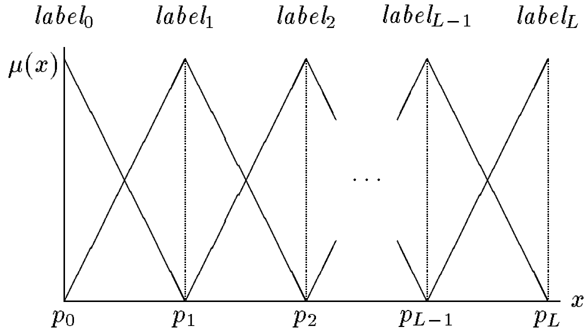

Figure 3: Triangle shape, densely assigned fuzzy set

3 Model

3.1 Fuzzy Inference

Single input and single output fuzzy inference model based on simplified fuzzy inference is used to obtain nonlinear mapping for each input variable. Nonmonotonicity of Kansei is accomplished by this mapping. The symbol of fuzzy inference is shown as in figure 2.

Simplified fuzzy inference is formalized as follows; Let $x \in \mathcal{X} \subset \mathcal{R}$ be the input variable of the model, and $s \in \mathcal{S} \subset \mathcal{R}^{+}$(positive real) be the output variable of nonlinear mapping performed by fuzzy inference. Rule set of fuzzy inference is denoted as follows;

$$\text{IF } x \text{ is } label_j \text{ THEN } s = w_j \ , \quad j = 1, 2, \cdots, R \quad (1)$$

where $label_j$ is the label of fuzzy set defined on input variable space $\mathcal{X}$, $w_j > 0$ is a singleton defined on output variable space $\mathcal{S}$, and R is the number of rules.

The labels are triangle shape fuzzy sets identified by

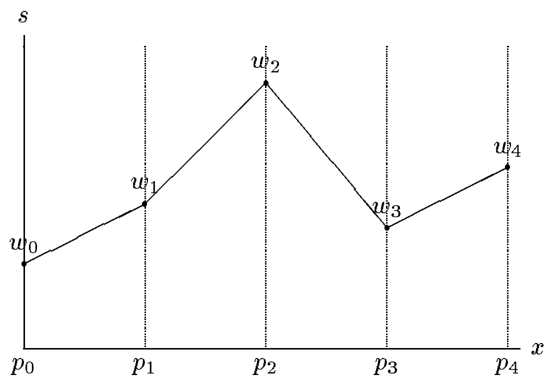

Figure 4: Nonlinear function by fuzzy inference

center position and two edge positions. Let L be the number of labels. Since we only treat single input single output case here, L is equal to the number of rules R. They are assigned densely as shown in figure 3 by forcing the restriction on center position and edge position of two adjoining sets to take the same value. Consequently, the center position parameters p_j, $j = 1, 2, \cdots, L$ are essential to identify these fuzzy sets.

Let μ_j be the membership value of j-th label, we can obtain the output value of fuzzy inference as follows;

$$s = \sum_{j=1}^{R} w_j \cdot \mu_j \qquad (2)$$

Thus, nonlinear function obtained by fuzzy inference is partial linear function as shown in figure 4.

When the input variable takes discrete value, input support S becomes a set whose members are the possible value of the input variable. Then, fuzzy set identified by $label_j$ becomes singleton that takes the membership 1 on the certain member of S.

3.2 Hierarchical Combination

The output variables of nonlinear mapping performed by fuzzy inference are recursively combined two by two as follows. Let s_1 and s_2 are arbitrary chosen two output variables of nonlinear mapping for a while. They are combined by a nonlinear function

$$s_{1,2} = k_{1,2} \cdot {s_1}^{a_{1,2}} \cdot {s_2}^{b_{1,2}} \qquad (3)$$

where $k_{1,2} > 0$ is assumed. Note that $s_1 > 0$, $s_2 > 0$ hold since $r_j > 0$ in fuzzy reasoning, and then we have

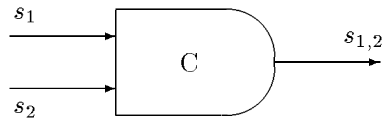

Figure 5: Symbol of combination unit

$s_{1,2} > 0$. We call this function "combination unit" since it makes compromise combination of variables s_1 and s_2. The combination unit is based on a nonlinear function

$$\tilde{s}_{1,2} = \tilde{a}_{1,2} \cdot s_1 + \tilde{b}_{1,2} \cdot s_2 + \tilde{k}_{1,2} \cdot s_1 \cdot s_2 \qquad (4)$$

which is called "Kolmogolov-Gabor polynomial". There is a research to use this function [2]. Based on the third term of eq.(4) and taking account into the power of each input variable separately, we obtain the function eq.(3). The symbol of combination unit is shown in figure 5.

After all output variables of fuzzy inference are combined, the combined variables are combined once again by the same unit. For example, if we have the variable $s_{1,2}$ and $s_{3,4}$, the output denoted by $s_{1,2,3,4}$ is calculated by

$$s_{1,2,3,4} = k_{1,2,3,4} \cdot {s_{1,2}}^{a_{1,2,3,4}} \cdot {s_{3,4}}^{b_{1,2,3,4}} \qquad (5)$$

This is shown in figure 6. When the number of variable is odd, combined variable $s_{1,2}$ and the other variable s_3 are combined as follows;

$$s_{1,2,3} = k_{1,2,3} \cdot {s_{1,2}}^{a_{1,2,3}} \cdot {s_3}^{b_{1,2,3}} \qquad (6)$$

This is shown in figure 7. By applying the above equations, we finally obtain a single output variable. We call this multiple-input-single-output model "sub-model".

3.3 Model structure

To have multiple output model, sub-model(single output models) are separately used for each output variable. The whole model is shown in figure 8. We call this "decomposed fuzzy model". Note that notation of signal and parameters are changed in order to give the identical denotation to each sub-model. For example, parameters contained by combination unit $k_{\cdot}$, $a_{\cdot}$, $b_{\cdot}$ are changed for sub-model (1) to $k_{\cdot}^{(1)}$, $a_{\cdot}^{(1)}$, $b_{\cdot}^{(1)}$, Parameters in fuzzy inference are also changed that $p_{i,j}^{(1)}$ shows the center parameter of i-th rule of j-th input variable of sub-model (1).

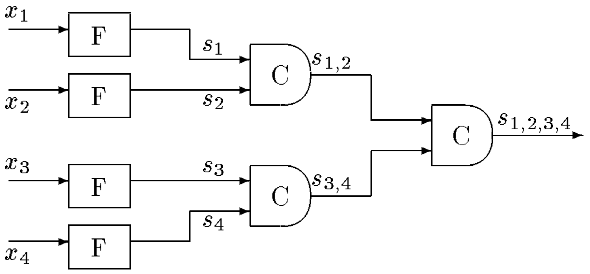

Figure 6: Hierarchical combination(even case)

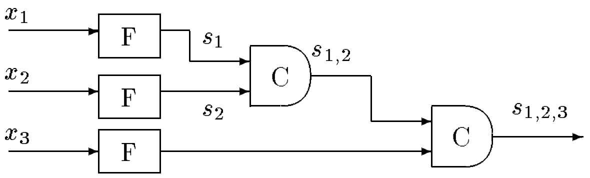

Figure 7: Hierarchical combination(odd case)

4 Estimation

Given data set, which consist of pairs of input-output variables

$$(\mathbf{x}_1, \mathbf{d}_1), (\mathbf{x}_2, \mathbf{d}_2), \cdots, (\mathbf{x}_N, \mathbf{d}_N), \tag{7}$$

where $\mathbf{x}_i$ denotes i-th input vector of n-dimensional, and $\mathbf{d}_i$ denotes i-th desired output vector of m-dimensional. Let $\mathbf{y}(\mathbf{x}_i)$ be output vector(m-dimensional) of the model with input vector $\mathbf{x}_i$.

In the proposed model, parameters to be estimated are $p_{i,j}^{(k)}$, $w_{i,j}^{(k)}$, $a_{\cdot}^{(k)}$,$b_{\cdot}^{(k)}$, and $k_{\cdot}^{(k)}$, where $i = 1, 2, \cdots, L$, $j = 1, 2, \cdots, n$, $k = 1, 2, \cdots, m$, and $\cdot$ denote appropriately defined combination of variables. They are simply denoted by a vector θ here. Error back-propagation learning algorithm is applied to the proposed model. The algorithm is formalized as steepest descent method with respect to the object function

$$E(\theta) = \frac{1}{2} \sum_{i=1}^{N} \mathbf{e}_i{}^T \mathbf{e}_i \tag{8}$$

where $\mathbf{e}_i$ denotes the error vector

$$\mathbf{e}_i = \mathbf{y}(\mathbf{x}_i) - \mathbf{d}_i \tag{9}$$

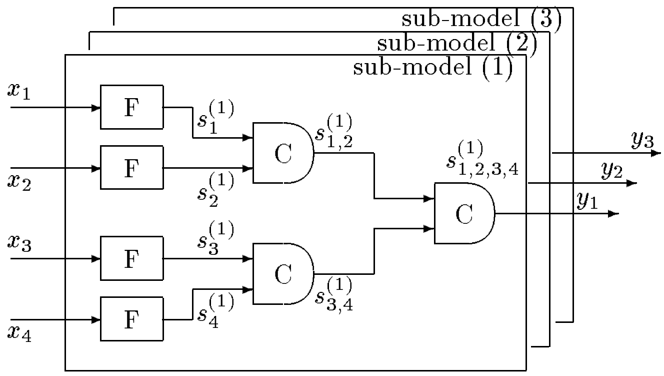

Figure 8: Decomposed fuzzy model

and $\mathbf{e}_i{}^T$ shows transpose of $\mathbf{e}_i$.

In the error back-propagation algorithm, the parameter vector is changed by

$$\theta_{n+1} = \theta_n - \varepsilon \frac{\partial E}{\partial \theta_n} \tag{10}$$

where k denotes the iteration, and ε is a step size parameter. Iteratively applying eq.(10) N times, we can finally obtain the estimated value of parameter θ denoted by $\hat{\theta} = \theta_N$.

5 Inverse Problem Solution

5.1 Hierarchical Combination

A scheme to solve inverse problem of combination unit is as follows. By defining

$$u_a \equiv s_a{}^{k_a}, \quad u_b \equiv s_b{}^{k_b}, \tag{11}$$

we can rewrite eq. (3) as

$$s_{a,b} = k_{a,b} \cdot u_a \cdot u_b \tag{12}$$

Let us consider that the output value $s_{a,b} = S_{a,b}$ is requested to change to $S_{a,b} + \Delta S_{a,b}$. If we fix the variable $u_a = U_a$, u_b can be changed as

$$U_b + \Delta U_b = \frac{S_{a,b} + \Delta S_{a,b}}{k_{a,b} U_a} \tag{13}$$

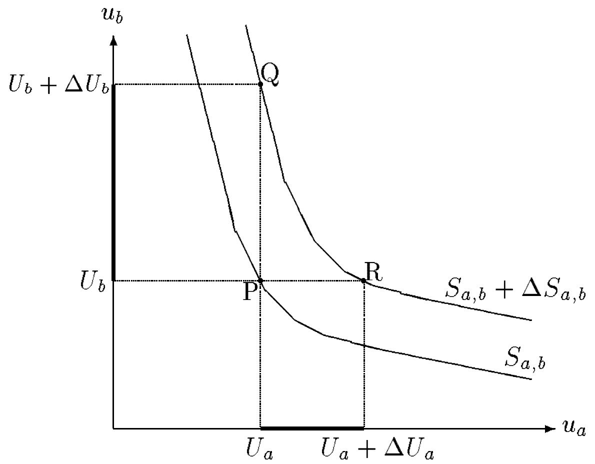

Figure 9: Inverse of Hierarchical Combination

On the other hand, when we fix u_b to U_b, we have

$$U_a + \Delta U_a = \frac{S_{a,b} + \Delta S_{a,b}}{k_{a,b} U_b} \tag{14}$$

By taking inverse of relationship defined by eq.(11), we can obtain solution sets $S_a + \Delta S_a$ and $S_b + \Delta S_b$ from $U_a + \Delta U_a$ and $U_b + \Delta U_b$, respectively.

The process to obtain inverse problem solution sets of combination unit is illustrated in figure 9. In the figure, P shows the initial position where u_a takes a value U_a, and u_b takes U_b. The output of combination unit takes value $s_{a,b} = S_{a,b}$. Note that there are many combination of input variables that take the same output value $S_{a,b}$. In the inverse problem, the output of combination unit is requested to take a value $S_{a,b} + \Delta S_{a,b}$. There are many combinations of input variables that satisfy the request. These combinations are shown as a curve $S_{a,b} + \Delta S_{a,b}$ in figure 9. Here we assume each input variable takes non-inferior value, i.e. $u_a \geq U_a$ and $u_b \geq U_b$ when $\Delta S_{a,b}$ is positive. Then we have an interval on the curve between Q and R in figure 9. By taking inverse image of this interval, we have the inverse problem solution sets of combination unit.

By applying this process to combination units from output to input, we finally obtain the solution set on the output of fuzzy inference.

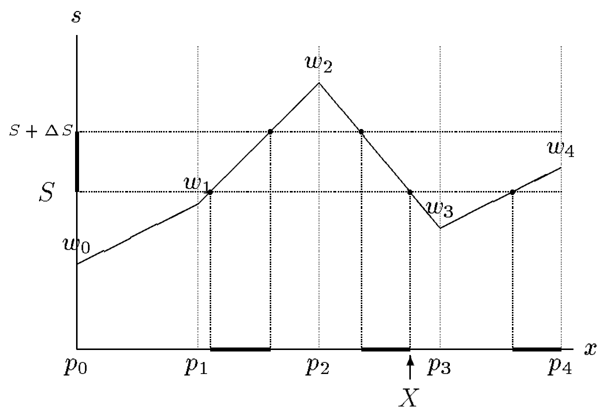

Figure 10: Inverse of Fuzzy Inference

5.2 Fuzzy Inference

A scheme to obtain solution set of fuzzy inference by giving a solution set on its output is described here. Since the nonlinear function by fuzzy inference is partial linear function, the inverse image of the function is obtained by taking the union of inverse images of each part where the function is linear. Note that the inverser image is not one to one, several intervals may be obtained. It is illustrated in figure 10. When the input of fuzzy inference takes discrete value, the inverse image becomes possible combination of input variable.

5.3 Whole Solution

Solution set of inverse problem can be obtained by the scheme shown above for each sub-model. To obtain a solution set of whole model is to take intersection of solution sets for all sub-model. This is illustrated in figure 11.

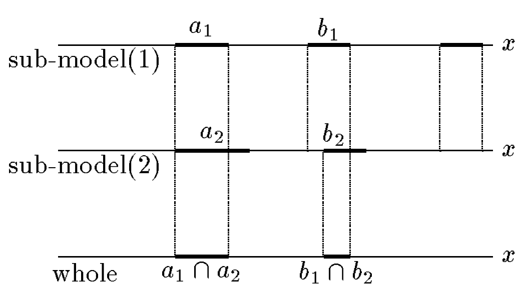

Figure 11: Whole solution

Table 1: Factor analysis result

factor	representative adjective pair			contribution rate
y_1	elegant	–	coarse	23.3%
y_2	heavy	–	light	14.3%
y_3	creative	–	usual	10.0%
y_4	warm	–	cold	7.8%
y_5	static	–	dynamic	6.7%
			total	62.1%

Table 2: Clustering result

group	feature					number of member
	y_1	y_2	y_3	y_4	y_5	
1	–	low	–	–	–	6
2	–	low	–	–	high	6
3	–	high	–	–	–	7
4	high	high	–	low	–	5
5	high	high	–	low	high	5
6	high	high	–	–	high	6

Table 3: Normalization of input and output variables

	value	range	normalized
x_1	hue	$[0, 360)$	$[0, 1)$
x_2	value	$[2, 9]$	$[0, 1]$
x_3	chroma	$[0, 14]$	$[0, 1]$
x_4	window type	tile	1
		sprayed tile	2
		steal panel	3
x_5	wall material	separate type	1
		continuance type	2

Table 4: Sum of squared error and correlation

	y_1	y_2	y_3	y_4	y_5
	sum of squared error				
L	0.5505	0.3630	0.5341	0.3246	0.2880
E	0.6418	1.0158	0.6537	0.6165	0.3535
	correlation				
L	0.6942	0.7316	0.9032	0.8500	0.7076
E	0.7079	0.7291	0.8379	0.7624	0.6899

"L" : learning, "E" : evaluation

6 Experiment

6.1 Measurement of Kansei

174 CG images, which are combination of 29 colors shown in table 7 in appendix C, three types of wall materials, and two types of windows, are used. 38 persons answer their feeling for adjective pairs with 7-stage-scale. The adjective pairs used here are shown in table 8 in appendix D, where the number of adjective pairs are 30. Then, the data matrix consists of 174×38 cases with 30 adjective pairs for each case.

Factor analysis is applied to the data by using the software "Statistica",StatSoft,Inc.,USA. We have obtained the five major factors with cumulative contribution rate 62.1% as shown in table 1. Correspondence of the adjective pairs to these factors are shown in table 8.

Clustering analysis has been applied to the data summed up the factor values with respect to CG images for each person. Dendrogram has been obtained by the analysis. Looking the dendrogram and by human subjective decision, we have obtained six groups as shown in table 2. In the table, features of each group are briefly shown by "high" or "low", where "high" means the factor is given the weight, and "low" is the opposite.

6.2 Estimation Result

For the 1st group shown in table 2, estimation has been done as follows. Firstly, the range of input variables are normalized as shown in table 3. Secondly, we make average for each the output variable with respect to the group member(6 person in case of the first group). Then we have 174 input-output pair for the group. Thirdly, we have split the pairs into two parts, learning set and evaluation set. The number of data for each data set is same in this experiment.

For the learning data set, we have applied the learning process of our model $100,000$ times with learning coefficient $\varepsilon = 0.001$. Evolution of sum of squared error of output up to $50,000$ iteration are shown in figure in appendix A for learning data set and evaluation data set, respectively. The final result of sum of squared error for each data set are shown in table 4. In the table, correlations between desired value and actual value are also shown.

The estimated parameters of fuzzy inference and combination unit are shown in table in appendix B. In these tables, parameters restricted to be positive are shown by their logarithm.

Table 5: Conditions for inverse problem

	Input	
	original value	normalized value
x_1	126	0.3500
x_2	7	0.7143
x_3	6	0.4286
x_4	sprayed tile	2
x_5	separate type	1

desired output				
d_1	d_2	d_3	d_4	d_5
0.6667	0.5000	0.4286	0.5714	0.6667
actual output				
y_1	y_2	y_3	y_4	y_5
0.6482	0.4813	0.4556	0.4990	0.6080
request				
Δy_1	Δy_2	Δy_3	Δy_4	Δy_5
0.07143	0.1429	-	-	-

Table 6: Inverse problem solution

sub-model(1)		
x_1	$[0.2247, 0.3500]$	$[0.7452, 0.7500]$
x_2	$[0.7143, 0.9866]$	
x_3	$[0.4286, 0.5000]$	
x_4	2	
x_5	1	
sub-model(2)		
x_1	$[0.3500, 0.5000]$	
x_2	$[0.7143, 0.9200]$	
x_3	$[0.4286, 0.5000]$	
x_4	1,2,3	
x_5	1	
whole model		
x_1	$[0.3500, 0.3500]$	
x_2	$[0.7143, 0.9200]$	
x_3	$[0.4286, 0.5000]$	
x_4	2	
x_5	1	

6.3 Inverse Problem Solution

Table 5 shows the conditions for inverse problem. We have assumed the input color 5GY(126 degree in hue angle), 7 value, and 6 chroma in Munsell color system. Wall material is sprayed tile, and window is separate type. Desired output and the actual output for this input is shown in the table. At the bottom of the table, customer's request is shown. Normalized value for each variable besides in the table.

Table 6 shows the result of the inverse problem. In the solution of sub-model(1), x_1 can take two intervals, x_2 and x_3 are single interval, and, x_4 and x_5 remain original values. On the other hand, in the solution of sub-model(2), x_1 can take only single interval, x_2 takes a interval different from sub-model (1), x_3 is the same interval, x_4 can take any type, and x_5 remains original values.

By taking the intersection between solutions of sub-model(1) and sub-model(2), we have obtained the whole solution as shown in the bottom of table 6. x_1 results the original value(0.35) since intervals only overlap on the point. x_2 takes the interval of sub-model(2) since the interval of sub-model(1) contains that of sub-model(2). The solution of x_3 is obvious since two intervals of sub-model(1) and sub-model(2) are the same. x_4 takes 2 since solution of sub-model(1) only takes that, and x_5 is the same value of both sub-models.

7 Conclusion

We have proposed a new model for Kansei design by using decomposed fuzzy model and inverse problem approach. The model has been applied to building exterior design. The input of the model is building attributes vector, and the output is a vector of factors obtained by SD technique. Simple experiment shows how is the inverse problem solution obtained.

For the future researches, there remain majorly two works; (1) to determine an unique solution from the interval, (2) to identify a group where the customer is in. We will construct a computer aided design(CAD) system using the proposed model.

Acknowledgement

Kansei data were measured by Power Engineering Research and Development Center, Tokyo Electric Power co., Japan.

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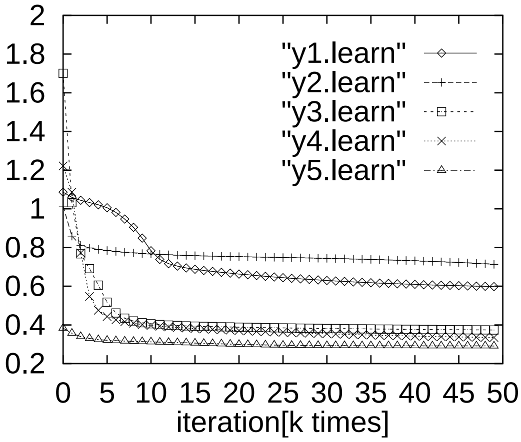
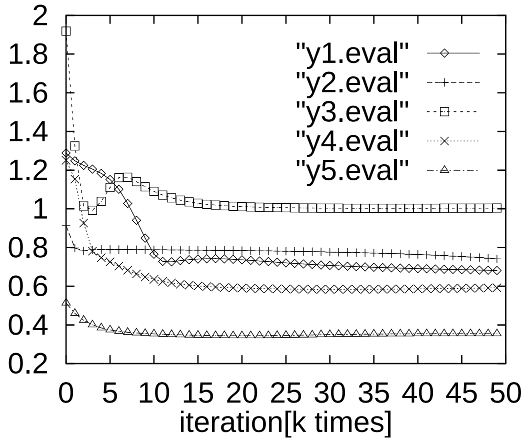
Appendix

A Evolution of sum of squared error





B Estimated parameters

	$\log w_1$	$\log w_2$	$\log w_3$	$\log w_4$	$\log w_5$		$\log k$	a	b
					sub-model(1)				
x_1	0.5398	1.1209	1.0029	1.0767	0.5398	$s_{1,2}$	-0.9368	-0.3503	-0.5120
x_2	0.8838	0.1902	0.8646	1.2535	1.7000	$s_{1,2,3}$	-0.8115	0.1539	-1.6878
x_3	0.1198	0.4726	1.3795	1.4131	1.4292	$s_{4,5}$	0.2764	0.2922	-0.2127
x_4	0.8975	0.8020	1.4528			$s_{1,2,3,4,5}$	0.7754	-0.4311	-0.3895
x_5	0.7608	1.0680							
					sub-model(2)				
x_1	0.0607	0.3866	1.3475	1.2379	0.0607	$s_{1,2}$	0.2433	0.7633	0.1503
x_2	0.7199	0.2827	0.8190	1.2476	1.7353	$s_{1,2,3}$	-0.6461	-0.0663	1.8332
x_3	0.1543	0.4700	1.2112	1.4487	1.5336	$s_{4,5}$	0.7690	-0.0182	1.7315
x_4	0.8705	0.6934	1.5163			$s_{1,2,3,4,5}$	-1.2947	0.4043	-0.4276
x_5	0.7484	1.0507							
					sub-model(3)				
x_1	0.1384	0.5644	1.3519	1.1614	0.1384	$s_{1,2}$	-0.2727	1.0523	-0.9505
x_2	-0.7447	1.4061	1.3029	1.2741	1.1554	$s_{1,2,3}$	-1.0404	0.1483	0.9010
x_3	-0.2101	1.0100	1.1672	1.2967	1.5295	$s_{4,5}$	0.3104	-0.0682	1.8151
x_4	0.8412	0.9808	1.4056			$s_{1,2,3,4,5}$	-1.1679	-0.8371	2.0221
x_5	0.8828	0.9714							
					sub-model(4)				
x_1	-0.0174	0.2256	1.2763	1.3654	-0.0174	$s_{1,2}$	0.4336	-0.5827	-0.4641
x_2	-0.1295	0.6650	1.4011	1.6074	1.1353	$s_{1,2,3}$	0.6106	-0.2891	-0.2302
x_3	-0.2841	0.6996	1.0907	1.5365	1.5292	$s_{4,5}$	-0.5790	-0.2004	-1.5157
x_4	0.7991	0.8661	1.4698			$s_{1,2,3,4,5}$	0.6120	-0.5634	-1.2183
x_5	0.8327	1.0057							
					sub-model(5)				
x_1	0.0438	0.7214	1.0928	1.3657	0.0438	$s_{1,2}$	-0.0659	-0.6362	-2.1748
x_2	-0.2013	0.6743	1.1815	1.4906	1.5060	$s_{1,2,3}$	-0.5264	-0.3277	1.2268
x_3	-0.0906	0.7176	1.1595	1.3370	1.6209	$s_{4,5}$	-0.4268	0.0394	-2.3152
x_4	0.8545	0.8608	1.4556			$s_{1,2,3,4,5}$	-0.3622	0.6514	2.1533
x_5	0.6956	1.0959							

C Color used for CG image

Table 7: Colors used for CG image

name	hue angle[deg]	value	chroma
N	0	7	0
		9	0
5R	18	5	6
		6	10
		8	4
5YR	54	3	2
		6	4
		7	12
		8	6
5Y	90	6	10
		7	4
		8	14
		9	3
5GY	126	5	2
		7	6
		9	4
5G	162	5	10
		8	4
5BG	198	7	8
		8	3
5B	234	4	8
		6	8
		8	4
5PB	270	6	8
		8	3
5P	306	6	8
		8	4
5RP	342	7	2
		7	8

D Adjective pairs

Table 8: Adjective pairs

adjective pair			factor
elegant	–	coarse	y_1
classical	–	popular	
familiar	–	unfamiliar	
weariless	–	wearily	
graceful	–	rude	
strained	–	casual	
clear	–	gloomy	
stable	–	unstable	
fashionable	–	unfashionable	
orderly	–	disorderly	
satisfied	–	unsatisfied	
heavy	–	light	y_2
cheerful	–	gloomy	
dense	–	dilute	
profound	–	superficial	
casual	–	formal	
creative	–	usual	y_3
interesting	–	uninteresting	
frugal	–	deluxe	
warm	–	cold	y_4
natural	–	artificial	
static	–	dynamic	y_5
delicate	–	rough	
urban	–	rural	none
calmly	–	incentive	
vivid	–	dull	
plain	–	showy	
cool	–	hot	
tasteful	–	tasteless	
sharp	–	blunt	