PLS-based approach for Kansei analysis

Tatsuro Matsubara* Yukihiro Matsubara* Shigekazu Ishihara† Mitsuo Nagamachi†
*Graduate School of Information Science, Hiroshima City University
†School of Pshychological Science, Hiroshima International University
*3-4-1 Ozuka-Higashi, Asa-Minami-Ku, Hiroshima, 731-3194, JAPAN
†555-36, Kurose Gakuendai, Higashi Hiroshima City, Hiroshima Prefecture, 739-2695, JAPAN
email:t_matsubara@lake.info.hiroshima-cu.ac.jp

***Abstract*—A residential garden contributes to mental health in modern life. Gardening is a common recreational activity. From the view of the Kansei engineering, designing the garden is a quite difficult subject. Since garden components such as stones and trees are widely diversified, then number of possible design elements becomes quite large. Meanwhile, evaluation samples that can be used for Kansei Evaluation are limited.**

Relations between Kansei word evaluation and design elements had been analyzed with Quantification Theory type I, which is a variation of a multiple regression model. Since QT1 is based on the least square method, number of evaluation samples should be larger than the number of design elements. Thus, QT1 is not applicable in this case.

Recently, PLS (Partial Least Squares) is becoming popular in the field of Chemometrics, which deal with extremely large number and interacted predictor variables. In this study, we utilized PLS for analyzing Kansei evaluation on residential gardens and their 89 design elements. Analyzing results of PLS and QT1 are compared. QT1 analyses were done on 5-fold design elements. Even when incorporating 89 variables, PLS 's multiple correlation coefficient was much higher than QT1.

Analyzing result was made into hand-made virtual reality Kansei engineering system. The system contains two projectors and a PC. 3D models of parts such as trees and stones are dynamically chosen and allocated in the scene. The system was based on originally developed 3D computation and rendering library on Java.

I. General Introductions

A residential garden is the small personal garden in the yard of a residence. At least it was common in Romans and spread in the Renaissance era. In Japan, private and temple garden has more than 1000 years tradition. In medieval age, art of tea became common culture for Bushi, Japanese warrior, then small (often courtyard) tea garden spread to Bushi residence.

In modern age of Japan from Meiji (1868-1912), Taisho (1912-1926), residential garden was popular for richer people, then gradually spread to common peoples houses [1].

In this modern world, people expect mellower, peace of mind, even curative atmosphere to the residential garden.

Revealing relations between mellow and curative Kansei to garden design elements helps garden designing which accustomed to a client. Realization of the design with 3D graphics will contribute to make ideal garden design. It will stimulate interaction between a client and a garden designer. The steps of this research are as follows;

- Survey of residential gardens
- Analysis of Kansei evaluation data of residential gardens
- Making a virtual reality system that assists realization of design from Kansei

Modern society has complex stress and pressures. Most of the people require stress management. Turning entire living environment into a curative environment contributes to design of healthy urban environment.

To study the garden in Kansei engineering methodology, there are several challenges. One is a large number of design elements. In this case, number of design elements is 32 items 89 categories. Although we have used 47 gardens for evaluation sample in Kansei evaluation experiment, the sample number is not sufficient for regression analysis which based on least-square method. We utilized PLS based analysis for this project.

Another challenge is building a virtual reality Kansei system. Available VR systems require large amount of budget, space and efforts for model building. To encourage Kansei VR system for gardening, the VR system should be low-budget and should base on common devices. In addition, model building has to be easier. Then, we have decided to make hand made VR system that can read and display 3D objects those are expressed in a common 3D format, OBJ.

Relations between Kansei word evaluation and design elements had been analyzed with Quantification Theory type I, which is created by Japanese statistician Chikio Hayashi in 1950s.

Evaluation values on a Kansei word are assigned to y (dependent) variable and design elements are assigned to x (independent) variables with dummy variables. In QT1, the qualitative variable such as product body color is called " item ". The variations of the item such like white / blue / red are called " categories ". Categories are expressed with dummy variables those have 1/0 value. Weights to the categories will be found with a multiple regression model. Computing method is solving (number of all categories - 1) simultaneous equations [2].

QT1 is a deterministic method because it is a variation of multiple regression model and its solving method uses least square method. Although QT1 is widely used, there are two defects: 1. Problem of sample size; QT1 incorporates (number of category - 1) dummy variables. In a multiple regression model, simultaneous equations could not solved when number of variables exceed to the number of samples. Kansei engineering situation has tens of samples, and many cases have the larger number of design variables. Then, the analyst has to divide design variables to do analysis. 2. Problem of interactions between x variables; if there are heavy interactions between x variables, analyzing result is distorted. The problem is known as multicollinearity in multiple regression analysis.

PLS (Partial Least Squares) is becoming popular in chemometrics. PLS has possibility to resolve above problems. In this study, we analyze personal garden Kansei engineering experiment data with PLS, and consider its analyzing ability.

In this paper, we present considerations on analysis ability of PLS with Kansei evaluation data of personal gardens. In the later part of this paper, analyzing result was made into handmade virtual reality Kansei engineering system. The system was built with two projectors and PC. 3D models of parts such as trees and rocks are dynamically chosen and allocated in the scene. The system deals with OBJ, most common format for 3D model data. The system was written in Java with original 3D computation and rendering library.

II. Kansei Evaluation Experiment

We had shot more than 150 photos of residential gardens at Nagano, Hokkaido and Hiroshima.

47 panoramic photos were chosen for evaluation. These photos were projected on the screen with a LCD projector. Subjects were 19 unpaid university students (13 male and 6 female). SD questionnaire contained 26 Kansei word pairs such as " calm in mind [ ] [ ] [ ] [ ] [ ] not calm in mind ". The evaluation was done in 2004. Figure 1 shows a panoramic photo sample.

III. Partial Least Squares

PLS was developed by Swedish econometrician Herman Wold and co-workers from middle of 1970s. The most popular area of PLS is Chemometrics from middle of 1990s. A typical example takes spectrum distribution on huge number of x.

Fig. 1. A photo of residential garden

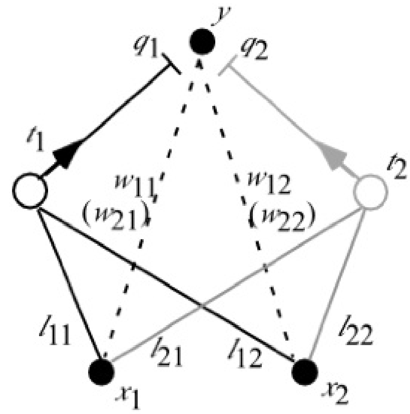

Fig. 2. Structure of PLS

In these applications, number of x ups to several hundreds and correlations between x variables are very high because of spectrum. On the other hand, y takes measured value such as temperature or PH, and sample number is tens at the most. Brereton (2003) shows such smaller sample size cases in Chemometrics [3]. Common multiple regression cannot deal with such data.

PLS uses several latent variables. There are s (number of samples) observations of objective (dependent) variable. These become vector y. There are p dimensional explanatory (independent) variables. These become vector x. There are number s of x, then become matrix X. The algorithm given below is based on Miyashita and Sasaki (1995) [4].

Figure 2 shows PLS mathematical approach. At the first step, $\mathbf{w}$, covariance vector of y and x is computed. The $\mathbf{w}$ is treated like eigenvector in principal component analysis. Second, latent variable $\mathbf{t}_1$ is introduced by

$$\mathbf{t}_1 = \mathbf{X}\mathbf{w}_1 \tag{1}$$

thus,

$$\mathbf{t}_1 = \sum_{k=1}^{p} x_{1k} w_k \tag{2}$$

Output from $\mathbf{t}_1$ is regarded as principal component score. Third, l_{11}, l_{12}, ... correlations between $\mathbf{X}$ and $\mathbf{t}$ (these compose vector $\mathbf{l}_1$) are repesented by

$$\mathbf{X} = \mathbf{t}_1 \mathbf{l}_1{}^{\mathrm{T}} + \mathbf{E} \tag{3}$$

where $\mathbf{E}$ is residual term. They correspond to principal component loadings (correlation between principal component score and original variable). Forth, q_1, relation between $\mathbf{t}_1$ and $\mathbf{y}$ is computed by

$$\mathbf{y} = \mathbf{t}_1 q_1 + \mathbf{f} \tag{4}$$

The q_1 is the result of single regression analysis (with no bias term), which takes $\mathbf{t}_1$ as an explanation variable and takes

$\mathbf{y}$ as objective variable. Fifth $\mathbf{X}$-$\mathbf{t}_1$-$\mathbf{y}$ relation can be computed. Sixth, second latent variable $\mathbf{t}_2$ is introduced and we compute $\mathbf{X}$-$\mathbf{t}_2$-$\mathbf{y}$ relation with the same procedure noted above. This time, $\mathbf{y}$ takes the residual of $\mathbf{X}$-$\mathbf{t}_1$-$\mathbf{y}$ model, and $\mathbf{X}_{\text{new}}$ takes residual of $\mathbf{X}$-$\mathbf{t}_1$-$\mathbf{y}$ model, which obtained by estimation by inverse way, that is

$$\mathbf{X}_{\text{new}} = \mathbf{X} - \mathbf{t}_1 \mathbf{l}_1{}^{\mathrm{T}} \tag{5}$$

and $\mathbf{t}_2$ is represented as

$$\mathbf{t}_2 = \mathbf{X}_{\text{new}} \mathbf{w}_2 = (\mathbf{X} - \mathbf{t}_1 \mathbf{l}_1{}^{\mathrm{T}}) \mathbf{w}_2 \tag{6}$$

As the result, relations between two latent variables and $\mathbf{y}$ or $\mathbf{X}$ are obtained. Finally, we get a regression equation by composing these relations.

The high dimensional x is projected onto smaller dimension orthogonal space. The relation between the projection and y is solved with simple regression. Thus, the dimensionarity problem (sample size problem) is solved. The projection procedure is similar to procedure of principal component analysis. Since the projection is linear transformation, regression coefficients can be computed. Thus, correlations between explanation variables do not cause the multicollinearity problem. The multicollinearity is also avoided since there is no need for solving simultaneous equations.

IV. PLS ANALYSIS OF PERSONAL GARDEN KANSEI EVALUATION DATA AND COMPARISON WITH QT1

The mathematical features of PLS are quite attractive, but there is no statistical pointer for acceptance of the number of x variables. Since this study is the first attempt to use PLS in Kansei engineering, we should consider its ability.

We have compared analyzing results of PLS and QT1, with Kansei evaluation data on 47 residential gardens. Design element table has 32 items and 89 categories. PLS implementation, which we used, was JMP 5.2 (SAS).

To analyze the data with QT1, we have divided design elements into 5-fold (23/9/18/28/11 categories). We performed QT1 on each division, thus we got 5 results. We compared multiple correlation coefficients (correlation between predicted y values and measured values) of QT1 and PLS. Even when incorporating 89 variables, PLS 's multiple correlation coefficient was much higher than QT1. Thus, PLS makes a model that fits the data better than QT1.

We obtained numerically excellent result with PLS. Figure 3 shows that the analyzing result seems nearly perfect fit to the data. Another side of the perfect fit is the overfit to the data. Overfitting to the data is picking up all of the (unwanted) deviation of the sample and it makes the model too complex. As the result, overfitted model becomes more specific than the generalized.

We also have compared QT1 result with PLS result in qualitative manner. Although PLS can compute with all 89 x variables as we shown in above lines, in this comparison we compute the model by adding variable in 5 steps. Step 1 used 22 variables, step 2 used 22+9=31 variables, step 3

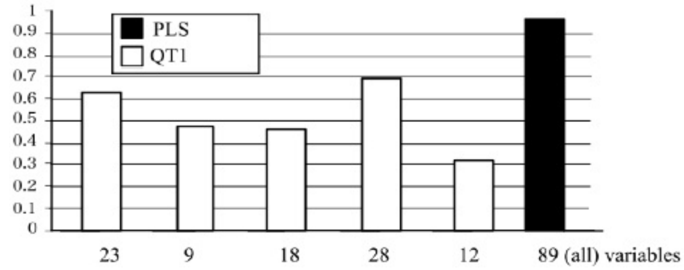

Fig. 3. Comparison between PLS and QT1 results: Multiple Correlation Coefficients

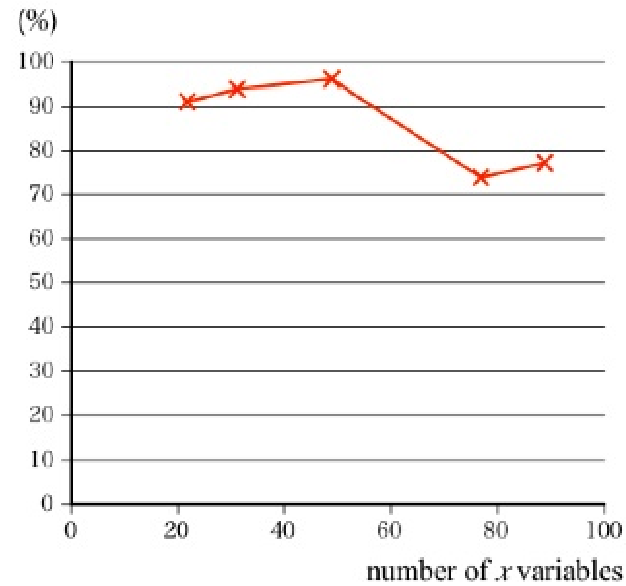

Fig. 4. Accordance with PLS and QT1

used 31+18=49, step 4 used 49+28=77, finally step 5 used 77+12=89 variables. The numbers of latent variables that used are four at step 1 and 2, six at step 3, 4 and 5. These numbers were decided to have best performance (smaller residuals) by several trials with different number of latent variables.

Then we have surveyed accordance of ranks of categories in each item, between PLS and QT1. Figure 4 shows the accordance along to the number of variables.

When the number of x variables exceeds the sample size, the accordance slightly decreases (right side of the Figure 4).

It seems that in the cases of smaller sample size, averaging effect is less, then smaller deviations reflecting to the result.

In many practical cases of KE, we can get numerically accurate model of relations between design elements and Kansei with PLS. In other word, analyzed result with PLS reflects smaller deviations (noise) by sample because of near perfect fit. PLS is very promising, but we have to read analyzing result carefully to decide the result reflects entire tendency or the particular sample.

One of analyzing result is as follows. " Curative " garden should have 2 big standing stones, more than 6 middle size stones aligned in not linearly, 6 to 10 small stones and stepping stones, type is modern Japanese, 1 pine tree and tall stone lantern should be arranged.

V. Building general Kansei engineering VR system

The second aim of this research is building virtual reality Kansei engineering system. Applying VR to Kansei engineering is very promising. We can present" virtual product "which is optimal for user 's Kansei based on Kansei evaluation and analysis. Stereo visualization of virtual product is ideal not only for precise reviewing but also for esthetic attractiveness.

There are 3 difficulties of making and utilizing VR system for Kansei engineering; dynamic composition, mobility and price. Common VR systems display complete scene. Meanwhile, Kansei engineering system is required for dynamic composition of a scene from parts along with the inference result. To show the most optimal design candidate for the intended Kansei, details of a design must be chosen from parts database and they should composed into a concrete design. Thus, the Kansei VR system has to have this dynamic composition function. Mobility is another requirement. For the public viewing of the 3D scene, larger scale system was commonly used. Since Kansei VR system should be used for realization of produce designs at the sites of R&D. Thus, the system hardware should be smaller. The last requirement is the price. Common VR system still costs higher, but to popularize the usage of VR at Kansei engineering, the price of the system should be lower price.

Our system can compose the entire scene or product from the detailed 3D parts with the result of Kansei analysis. It consists of common PC, portable screen, two home theater LCD projectors and polarized glasses. Its cost is around 500,000 yen (4150 USD).

In the present paper, we describe a personal garden Kansei VR system based on the PLS analysis result which was shown in the former part of this paper. VR immersive experience is required especially for garden design, because usually we have enjoyed the garden from inside of it. In addition, there are differences between client and garden builder on their knowledge and recognition of garden design. Although the garden builder can imagine how the garden will be from his/her expertise, but the client cannot do. Immersive presentation will fill the gap between builder and client.

A. VR system outline

Although we had been studied and built various handmade 3D CG or VR systems using Java3D, Xj3D and Max/Jitter, there are many problems [5].

Java3D had made by Java team of Sun. Java3D cannot import common 3D object files (such as OBJ, DXF, 3ds) and / or texture pattern files. A scene graph, complex tree structure graph is required for render 3D object with Java3D. Thus, it is very hard to both importing objects and adding texture to the object in scene graph. Then, its expandability for an actual working system is low, which can deals with larger number of textured objects. OpenGL is common API for 3D graphics game. Though OpenGL has quick drawing methods for 3D object " seams " of the texture are apparent on polled objects such as cylinders and spheres. OpenGL deals only are virtual drawing device. Thus drawing is done are window by one window when two or more windows are used. This causes seriously showing on Stereo vision. Another deficit of OpenGL is its low-level design. Definitions of lighting and rendering textured 3D objects are very complicated.

In this research, we have built original 3D CG framework (EXEV-J, Easy eXpandable Environment for Vr on Java) , which does not depend on common framework, such as OpenGL and Java3D. The EXEV-J is the base of Kansei VR system which was built in this research. EXEV-J was written in Java, thus it runs many OS and machines.

To solve problems those have written on above lines and ensure expandability and versatility, the developed system has " loader " which read and interpret general 3D object file OBJ. And the system has many functions those are required for 3D representation, such as transformation of the polygon model coordinates (e.g., coordinate system for local, world, viewpoint, clip and screen), rasterize of the rendered scene, color sampling and mapping from texture file. System builder should prepare only texture data and 3D object data in OBJ format, made with common 3D CG graphics programs (e.g., 3D Studio MAX, MAYA, Blender, MetaSequoia, etc.).

We will explain on 3D CG real time rendering framework. Canvas class, which is a basic GUI component of AWT graphics of Java was utilized for displaying rendered scenes. Then, all of standard GUI programming of Java can be utilized. We have implemented stereo view and scene manipulation with mouse and keyboard. Workflow of K3DCanvas, extended " Canvas " class is shown in the Figure 5.

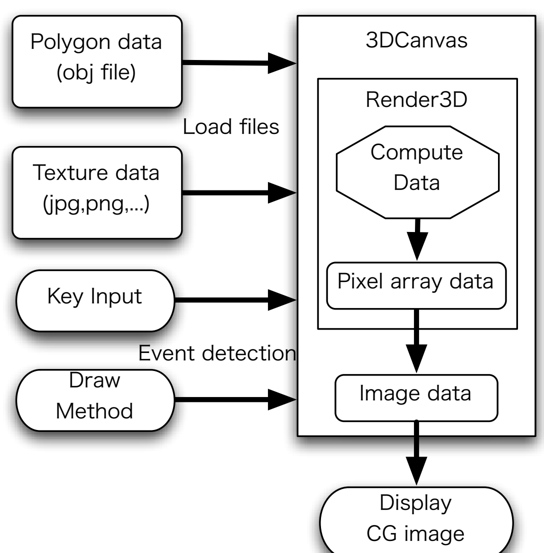

Fig. 5. Workflow of K3DCanvas

K3DCanvas includes Render3D, which shows image in canvas from 3D polygon data and texture. It contains large matrix computation. For realtime rendering computation, all images are expressed as pixel color data matrix. K3DCanvas sets polygon data and texture data on Render3D, and it shows rendered data matrix as pictures. It also handles events of key pressing and (re-)draw commands, for expressing moving view points and 3D CG drawing. Kansei VR system uses K3DCanvas for 3D CG computation and showing images.

Figure 6 shows our framework of Kansei VR System for residential gardens. The system has different databases; category scores, design element table and 3D object & texture data. From a client 's choice of a desired Kansei word, most suitable design element was selected. A category (valiant) has a maximum category score was selected at each design item. Then, the system obtains polygon and texture of the corresponding type of trees and stones from databases. Selected polygon and texture data are passed to K3DCanvas of right and left eye. K3DCanvas send draw command to Render3D. Then, viewer can see stereo vision of proposed garden design by real-time rendering. A walk-through type moving view is also equipped. In addition, this system can change viewpoints and add a new viewpoint, thus this system not only can perform single or stereo view but also all-around view for immersive VR system.

Figure 7 shows the rendered stereo image which correspond to " curative ".

VI. Conclusion

The aims of this study were expanding Kansei - design elements analysis methodology with PLS, and building a Kansei VR system with originally developed 3D computation framework.

PLS based analysis has shown excellent results under the small sample situation. A garden Kansei VR system was built from the analyzing result with PLS. The system was built on our original 3D computation framework in Java. Since its computation was rapid, its interactivity was excellent. With these research results, Kansei engineering methodology can be applied for more complexed designing. Visualization of the analyzed results can be shown in details.

Acknowledgement

Early part of this study was supported by Grant-in Aid for Scientific Research 2005-2006 (C) 17500155.

References

[1] Seike, K. Kudo, M. and Engel, D.H., A Japanese touch for your garden: Revised and expanded edition, Kodansha-International, Tokyo, 2008.

[2] Hayashi, C. On the prediction of phenomena from qualitative data and the quantification of qualitative data from the mathematico-statistical point of view, Annals of the Institute of Statistical Mathematics, 2(3), 69-98, 1952.

[3] Brereton, R. Chemometrics, Wiley, Chichester, England, 2003.

[4] Miyashita, Y. and Sasaki, S., Chemometrics-Chemical pattern analysis and multivariate analysis, Kyouritsu Publishing, Tokyo, 1995 (in Japanese).

[5] Nakahara, M., Ishihara, S., Nagamachi, M. and Ge, Qi-Wei, PLS analysis of Kansei evaluation data and hand-made VR Kansei engineering system, Proc. of International Conference on Kansei Engineering and Emotion Research 2007, 2007.

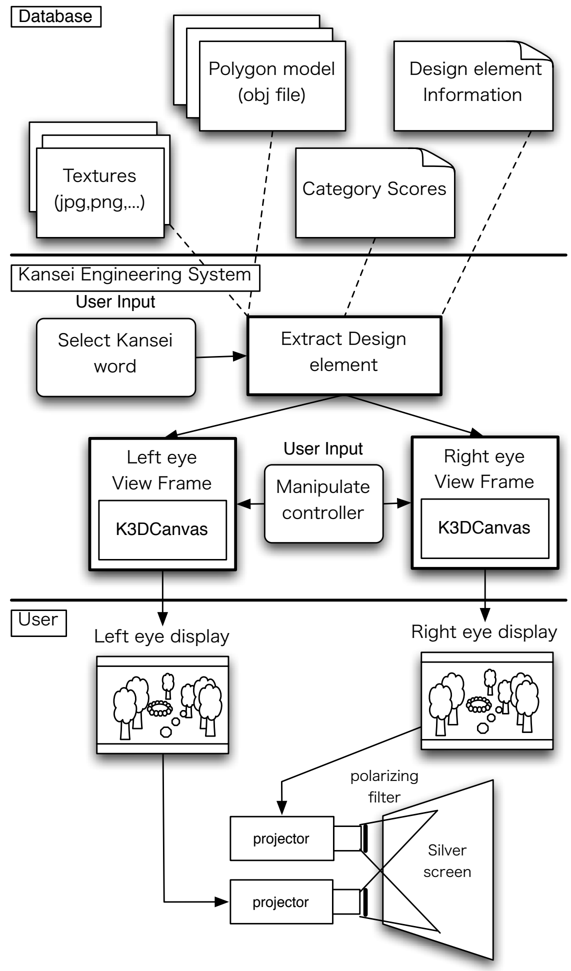

Fig. 6. Framework of Kansei VR system

Fig. 7. Image of " curative " residential garden