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Research Article

Kansei Analysis of the Japanese Residential Garden and Development of a Low-Cost Virtual Reality Kansei Engineering System for Gardens

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Residential garden design using Kansei engineering is a challenging problem. Landscaping components, such as rocks, trees, and ponds, are widely diversified and have a large number of possible arrangements. This large number of design alternatives makes conventional analyses, such as linear regression and its variations like Quantification Theory Type I (QT1), inapplicable for analyzing the relationships between design elements and the Kansei evaluation. We applied a partial least squares (PLS) model that effectively deals with a large number of predictor variables. The multiple correlation coefficient of the PLS analysis was much higher than that of the QT1 analysis. The results of the analyses were used to create a low-cost virtual reality Kansei engineering system that permits visualization of garden designs corresponding to selected Kansei words. To render complex garden scenes, we developed an original 3D computation and rendering library built on Java. The garden is shown in public-view style with stereo 3D graphic projection. The rendering is scalable from low to high resolution and enables drop object shadowing, which is indispensable for considering the effect of daytime changes in insolation. Visualizing the garden design based on Kansei analysis could facilitate collaboration between the designer and customer in the design process.

1. Introduction

"Kansei" is a Japanese word corresponding to "feelings" or "impression." Kansei engineering originated with Nagamachi about 30 years ago and is a method to convert customers' ambiguous ideas about products into a detailed product design and thereby to assist designers by providing guidance for product development that is in tune with customers' Kansei. It also helps customers choose from a variety of products those that fit their Kansei.

Kansei engineering procedures are based on psychological evaluation and multivariate analyses. This technique has advanced by incorporating artificial intelligence approaches, such as neural networks, genetic algorithms, and rough set theory, and by including various computer graphics (CG) techniques such as 3D CG and virtual reality (VR). Kansei engineering has been introduced into many industries worldwide, such as the manufacture of automobiles (e.g., Mazda Miata, MX5 in Europe), construction machines (KOMATSU), forklifts (BT industries), electric home appliances (SANYO), welfare, and home products (PANASONIC) (Nagamachi et al. [1–7]).

The standard methodology of Kansei engineering includes an evaluation experiment followed by statistical analysis of the obtained data. The most common implementation involves three steps: (1) selection of Kansei words, which entails collecting and choosing adjectives (e.g., "warm") and domain-specific jargon; (2) the Kansei evaluation experiment, which is a psychological evaluation of customer perceptions of various products and product samples using a questionnaire that contains many Kansei words; (3) multivariate analyses of data from the evaluation experiment, such as principal-component analysis or derivative methods that are then used to extract the Kansei structure. Quantification Theory Type I (QT1), a variant of multiple regression analysis that can take qualitative (nominal) variables as predictor variables, is commonly used to analyze relationships between the Kansei words and product-design elements.

Derived relationships between Kansei and design are rewritten as a set of inference rules that are then used in the Kansei engineering system. The system takes Kansei words as inputs, then, using the rules, infers the corresponding design elements, and draws a composite of them as an entire design graphic. During product development, the Kansei engineering system provides a common understanding of consumer Kansei to designers, merchandisers, and managers [8, 9]. It also helps the consumer to make a satisfying purchase by facilitating the selection of options from a large menu of choices. We have been developing Kansei engineering systems for the design of women's suits, interiors of passenger vehicles, construction machines, entry doors, and other uses [7].

2. Japanese Residential Garden Design and Challenges for Kansei Analysis

From its inception more than thirty years ago, Kansei engineering has been utilized for residence design [10]. Because there are so many alternative design elements in both residential and residential area design, a comprehensive mental image of the design is often difficult for a consumer to envision. Kansei engineering provides a powerful tool to address this problem.

The residential garden has a long and rich history, which has given rise to mental constructs that have varied widely over time. A residential garden was common among the Romans and became widespread during the Renaissance. In Japan, private and temple gardens are imbued with more than a thousand years of traditions. For instance, during the medieval age, the tea ceremony became a common cultural tradition of the Bushi, or Japanese warrior, and a Bushi residence inevitably included a small tea garden. In the modern age of Japan, during the Meiji (1868–1912) and Taisho (1912–1926) eras, the residential garden became popular among the wealthy, then gradually spread to the houses of the common people [11]. Today, people expect a mellow, peaceful, even curative atmosphere in the residential garden.

Revealing the relationships between customers' Kansei and garden design elements, Kansei engineering helps garden designers to customize clients' garden designs. Visualization of the design using 3D graphics contributes further to the ideal garden design, as it stimulates interaction between the client and garden designer, and the client can choose design elements that foster a particular mood (i.e., corresponding to particular Kansei words).

In the research reported here, we followed the following steps: (1) a survey of existing residential gardens; (2) a Kansei evaluation of sample gardens followed by multivariate analysis of the evaluation data; (3) creation of a virtual reality system to assist visualization of garden designs based on Kansei. To apply Kansei engineering methods to garden design required overcoming a number of challenges. One was the large number of potential design elements. Another was the technical details of visualizing the results (see Section 3). Considering the first challenge, the case-design element table contained 32 design items (e.g., the kinds and number of trees, allocation of stones, etc.), and the alternative elements (e.g., large, medium, or small landscaping rocks) comprised a total of 89 categories. Although we used 47 gardens as evaluation samples in the Kansei evaluation experiment, this sample number is insufficient for multiple regression analysis based on the least squares method.

Relationships between Kansei words and design elements are commonly analyzed using QT1, which was created by the Japanese statistician Chikio Hayashi in the 1950s [12]. Evaluation values of a Kansei word are assigned to objective variables, and design elements are assigned to explanatory variables. In QT1, the qualitative variable (e.g., product color) is called an "item." Variations in the item (e.g., white, blue, or red) are called "categories." Categories are expressed using dummy variables that have a value of one or zero. Weights assigned to the categories are determined using a multiple regression model. The computation method involves solving simultaneous equations equal in number to the number of all categories less one [12]. QT1, therefore, is a deterministic method because it is a type of multiple regression model and employs the least squares method. Although QT1 is widely used, it has two shortcomings. The first is the problem of insufficient sample size. In a multiple regression model, simultaneous equations cannot be solved if the number of variables exceeds the number of samples. In Kansei analysis, it is often the case that the number of design variables exceeds the number of samples. This is particularly true in the case of garden design. The problem of small sample size has been addressed by statisticians (e.g., [13]); to properly do the analysis, the analyst has to divide the design variables into groups, effectively increasing the relative sample size. However, dividing variables into groups greatly complicates the assignment of weights to the variables. The second shortcoming is the problem of interactions among the explanatory variables. If there is a high degree of correlation among the variables, the result of the analysis is distorted, a problem known as "multicollinearity" in multiple regression analysis.

To overcome the shortcomings inherent in multiple regression methods like QT1, a number of approaches have been developed. Neural networks with a multilayered perceptron (MLP) structure and a backpropagation (BP) learning algorithm can approximate nonlinear versions of multiple regression analysis, logistic regression analysis, and discriminant analysis (i.e., [14, 15]). Unfortunately, because the learned result is massively distributed, extracting the salient relationships between the explanatory and objective variables is difficult. This difficulty is caused by the nature of the BP algorithm to revise connections not currently used [16]. MLP with BP networks are suitable, therefore, only for a "black box" in which the extraction of relationships is not needed. We examined BP learning in the late 1980s and

Table 1: Traditional and new analysis methods.

Traditional analysis methods	Modern methods
Principal component analysis	PCAnet (neural networks)
Cluster analysis	ART1.5-SSS, arboART (neural networks)
Multiple regression analysis,	PLS (multivariate analysis)
QT1	Rough Set Analysis, Genetic Algorithm
	(Nonlinear optimization)

found difficulties in its use as an analyzer. Consequently, we used and improved neural networks that have linear units and no intermediate layers to perform cluster analysis [17] and hierarchical cluster analysis [18, 19], and we showed that they were more precise than traditional methods in their clustering. We also used principal-component analysis networks (PCA nets) [20], which have great flexibility for adding data without recalculating the entire dataset [21] (see also Chapter 6 of [7]). Rough set theory [22] (see also chapter 7 of [7]) and genetic algorithms [23] were also used and expanded for the analysis of relationships between exploratory variables and an objective variable. These approaches yield better results than do multiple regression analysis and QT1. These approaches are summarized in Table 1.

In this study, we analyzed Kansei data using a recent advance in statistical methodology, namely, partial least squares (PLS), a kind of structural-equation modeling technique. This method is becoming popular in the field of chemometrics [24, 25], as it has the ability to resolve problems resulting from small sample size and multicollinearity. The results of PLS analysis are readily comprehensible because the method is based on linear algebra and basic statistical techniques such as covariance and regression. The details of PLS are discussed in Section 4.

3. Virtual Reality (VR) Applications in Kansei Engineering and Requirements for a VR System

3.1. Industrial Applications of VR. Serious industrial application of VR began in the mid 1990s. At that time, the trend was to convert CAD/CAE data into VRML or IGES and display them [26, 27]. Most of the systems were developed to assist mechanical design; typical applications included automobile manufacturing [28–30], simulation of a production system in a factory, ergonomic evaluation, and education [31, 32]. Displayed objects had no or poor texture, and a solution for the lack of texture was sought (e.g., [29]). Expensive computers from Silicon Graphics were dedicated to rendering, and a head-mounted display (HMD) was commonly used.

Ten years later, a book edited by Talabă and Amditis [33] surveyed the industrial applications of VR. A large part of the VR system was replaced by a PC. Zimmermann [34] noted the 10-year progress at Volkswagen. Resolution became more than 1600 × 1200 pixels, and models had textures. Along with a higher resolution, a projection-type display became popular. Approximately one-third of the vehicle development process utilized VR. Amiditis et al. [35] reviewed various industrial areas. The autoindustry was the biggest user of VR technology, VR was gaining in popularity in the aviation industry, and it was showing promise in the area of technical training. Despite its large potential, however, VR is still underutilized in architecture and civil engineering.

3.2. VR Applications in Kansei Engineering. The first Kansei engineering system to use 3D real-time graphics was one for the development of an office chair. The system was built as part of a joint study with Nissan Motors. The system included analyzed results from 50 different design alternatives (categories) based on 16 design elements (items), such as back shape and base geometry, and presented an optimal office chair design from the input of Kansei words. This system used MacRenderman (Pixar Inc., 1991) as the rendering software. Although it took considerable time to produce a rendering, the resulting figure had only simple shading [36].

The largest application of VR for Kansei engineering was "Virtual Reality for Vivid A&I Space" (ViVA), a system for the custom design of kitchens. It was built by Panasonic (at that time Matsushita Electric Works, Ltd.) in the 1990s. Initially, researchers interviewed 61 customers about their lifestyles (e.g., frequency of kitchen use, family size, etc.) and performed a Kansei evaluation. The Kansei data were analyzed using principal-component analysis, factor analysis, cluster analysis, and QT1. The system contained a database of over 200 Kansei words and 18 design components. Design knowledge from a large base of cumulative data from around 10,000 clients was also incorporated into the database. The ViVa system could handle approximately 30,000 different kitchen product data.

The first version of the system went into operation in October, 1991, at the Shinjyuku showroom. When the customer visited the showroom, she or he was first asked about the dimensions of the room in question and the customer's height, information needed to select an appropriate overhead rack. Next, the customer answered a questionnaire about the family's lifestyle and the Kansei they hoped to realize. The system then presented a detailed, custom plan for the kitchen (layout, cabinet type and color, floor color, counter height, etc.) based on their preferred Kansei words such as "elegant" and "convenient." The system presented the composed kitchen scene in VR. The VR experience permitted the customer to examine the layouts of parts such as the cupboards and dishwasher, and they could change components, such as the size of the walls, the arrangement of appliances, and materials. By providing a concrete image, the VR system facilitated the customer's involvement in a collaborative design. After a decision was reached concerning the design details, an order sheet was automatically generated from the system's product database and sent to the factory [37, 38].

The first version of the ViVA system incorporated a Sun workstation, which ran CAD and the Body Electric VR system (VPL Research, Inc.) on a Silicon Graphics IRIX and Macintosh platform. As the largest industrial VR system of the time, the ViVA system and its hardware cost over \$500,000 USD. The VR scene was presented using both HMD and projection, and the scene was rendered with texture mapping. Later, a scaled-down version was built for the PC [39, 40]. The ViVA system and its successors became popular among both customers and the media. Nomura and Sawada [40] mentioned that fifty-five percent of kitchen purchases had utilized the system. VR makes two major contributions to Kansei engineering [6, 41]. One is the simulation and competency trial of the candidate design, which would otherwise be costly to build. In 1985, we built HULIS, the first Kansei engineering system for home interiors [2, 10]. Without HULIS, it would be very expensive to build a model and conduct testing for home interior design. Presenting a concrete image using sophisticated computer graphics is both rapid and cost-effective.

The second contribution made by VR is the facilitation of customer decision making. It is difficult for untrained people to fully visualize a house or kitchen from small photographs in a catalogue. There are countless options in home and kitchen design. Customers often complain about the difference between their imagined scene and what they actually got. When a customer and designer plan a building together, the process is facilitated when a concrete scene can be presented and various examining options are offered. With VR, such interaction between the designer and the customer is achieved.

3.3. Requirements for a Garden Kansei VR System. Because trees, plants, rocks, stones, and ponds vary widely, a residential garden has a very large number of design items. Once a garden is built, changing the design requires considerable effort and cost. Thus, a VR-based Kansei engineering system, which would facilitate customer participation in the design process, is expected to lead to greater customer satisfaction.

There are several requirements that an effective VR rendering engine must meet. The first is viewpoint. When enjoying a garden, one's viewpoint is not fixed. One walks around the garden and sees components from a variety of angles. Thus, to fairly represent a garden, the viewpoint should move in the scene. Second, trees are a crucial component of the residential garden and should be expressed in detail. This means the system has to be able to handle a large number of polygons to render the scene in high resolution. Blach [42] pointed out that one of the future directions of VR applications is the handling of a large number of polygons in complex scenes using realistic shading. In their book on VR applications development, Craig et al. [43] presented examples of richly textured scenes rendered by advanced VR systems. Third, the ambience of a garden changes throughout the day due to mevement of the sun. Therefore, illumination of object surfaces and their shadows should be shown in the rendered scene. A fourth requirement of a VR system is low price. Garden builders are usually small firms, and the price of the system must be affordable. To achieve these objectives, we built a rendering engine to run on a PC.

Lin and Zhang [44] pointed out that aesthetics have to be considered in Kansei engineering procedures. In Japanese residential garden design, the fundamental aesthetics include In and Yo (contrast), Shibumi (nature in the wild), Yugen (enveloping presence), Wabi (old), and Sabi (solitude) [45]. In the long tradition of Japanese garden design, many rules have been established for realizing these aesthetics. For example, a rock is not placed alone. In most cases, rocks are placed in a group in several types of combinations. The allocation of rock groups is generally decided based on the relationship between the house and garden (e.g., [11, 44–46]). These aesthetic rules are incorporated into our system through the use of layout templates.

In this paper, we consider several aspects of PLS analysis of Kansei evaluation data of personal gardens. Then, we describe a scheme of a handmade, virtual reality Kansei engineering system. The system as built includes two projectors and a PC. Component parts of the garden design, such as trees and rocks, are dynamically chosen and allocated in the scene and modeled in 3D. The system deals with OBJ, the most common format for 3D modeling data. The system was written in Java with an original 3D computation and rendering library.

4. Partial Least Squares

PLS was developed in the mid 1970s by the Swedish econometrician Herman Wold and his colleagues. Beginning in the 1990s, PLS has been applied to the field of chemometrics. A typical example is a spectrum in which the x variable includes a large number of instances. In these applications, the number of instances of x may be several hundred, with a very high degree of correlation between the x and y variables. On the other hand, the y variable is a measured value, such as temperature or PH, and the sample number is, at most, in the tens. Brereton [24] shows cases of such small sample size in chemometrics. Common multiple regression methods cannot deal with such data.

PLS uses several latent variables (Figure 1). There are s (number of samples) observations of an objective variable. These become vector $\mathbf{y}$. There are p dimensional explanatory variables. These become vector $\mathbf{x}$. Number s of $\mathbf{x}$ then become matrix $\mathbf{X}$. The algorithm given below is based on [25].

At the first step, $\mathbf{w}$, the covariance vector of $\mathbf{y}$ and $\mathbf{x}$, is computed. The value $\mathbf{w}$ is treated like an eigenvector in principal-component analysis. Second, the latent variable t_1 is introduced. Output from t_1 ($t_1 = \Sigma x_{ik} w_k$, thus $\mathbf{t}_1 = \mathbf{X}\mathbf{w}$) is regarded as the principal-component score. Third, l_{11} and l_{12}, correlations between $\mathbf{x}$ and t_1 (these compose vector $\mathbf{l}_1$), are computed. They correspond to principal-component loadings (the correlation between principal-component score and original variable). Fourth, q_1, the relationship between $\mathbf{t}_1$ and $\mathbf{y}$, is computed. The value of q_1 is the result of a single regression analysis (with no bias term), which takes $\mathbf{t}_1$ as an explanation variable and takes $\mathbf{y}$ as an objective variable. Fifth, the x–t_1–y relationship is computed. Sixth, the second latent variable t_2 is introduced,

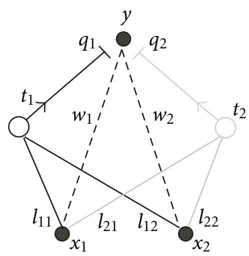


Figure 1: Structure of PLS.

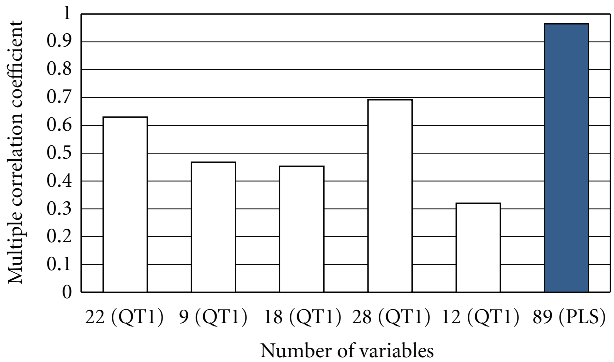


Figure 2: Comparison between PLS and QT1 results: multiple correlation coefficients.

and the x–t_2–y relationship is computed following the same procedure as in steps 1 to 5. This time, however, y takes the residual of the x–t_1–y model, and $\mathbf{X}$ takes the $\mathbf{X}$ residual of x–t_1–y model, which is obtained by estimation using the inverse method ($\mathbf{X}\text{new} = \mathbf{X} - t_1\mathbf{l}_1^{\mathrm{T}}$). As a result, the relationships between two latent variables and y or x are obtained. Finally, we get a regression equation by composing these relations. This entire process is called PLS regression.

The high-dimensional x is projected onto a smaller dimensional orthogonal space. The relationship between the projection and y is solved with simple regression. Thus, the dimensionality problem (small sample-size problem) is avoided. The projection procedure is similar to the procedure of principal-component analysis. Because the projection is a linear transformation, regression coefficients can be computed. Accordingly, correlations between explanatory variables do not cause a multicollinearity problem. The multicollinearity is also avoided because there is no need to solve simultaneous equations.

5. 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 explanatory variables. Given that this study was the first attempt to use PLS in Kansei engineering, we needed to consider its suitability for this function.

5.1. Kansei Evaluation Experiment. Of more than 150 photographs of residential gardens taken in three different parts of Japan, (Nagano, Hokkaido, and Hiroshima), 47 were chosen for evaluation. The panoramic photographs were projected onto a screen using an LCD projector. The experimental subjects were 19 unpaid university students (13 males and six females). The semantic differential questionnaire contained 26 Kansei word pairs such as "calm in mind [ ] [ ] [ ] [ ] [ ] not calm in mind." These Kansei words included basic Kansei words as well as Kansei words chosen by 11 professional garden or landscape architects. The evaluation was done in 2004.

We investigated and organized the design elements of typical residential gardens. There were 32 items (variables), and 89 total categories (variations of each items). The items were Large/Middle/Small Rock, Rock Composition, Gravel, Stepping Stone, Brick Paving, Tile Paving, Stone Lantern, Tsukubai (stone water basin), Stone Bridge, Tall Tree, Middle-sized Tree, Azalea, Ground Cover, Lawn, Wood Set, Wood and Stone Set, Wood and Lantern Set, Bamboo Fence, Wood Fence, Pine, Shakkei (borrowed scenery), Pond, Area, Landscape Type, Waterfall, Table, Ornaments, and Japanese/Western/Mixed Style. Each item had two, three, or four categories (alternatives).

To use these categorical (qualitative) variables as explanatory variables in PLS regression, we encoded them as binary coding (zero or one) according to whether the variable was true or not for a particular sample (garden), as shown in an abbreviated table of the design elements and samples (Table 2). The Kansei evaluation value of a Kansei word (averaged across subjects) for each sample was assigned to the target variable.

5.2. Comparison between PLS and QT1. We analyzed the Kansei evaluation data from 47 residential gardens using both PLS and QT1 and compared the results. The design element table contained 32 items and 89 categories. The PLS implementation software that we used was JMP 5.2 (SAS Institute).

To analyze the data using QT1, we divided the design elements into 5 groups containing 23, 9, 18, 28, and 11 categories, respectively. We performed a QT1 analysis separately on each group; thus we obtained five results. We compared the multiple correlation coefficients (i.e., the correlation between predicted and measured y-values) obtained using QT1 versus those obtained using PLS. Even with 89 variables, the PLS analysis yielded a multiple correlation coefficient of 0.965, a much higher value than those obtained with the QT1 analyses (0.63, 0.468, 0.453, 0.692, 0.32). Thus, PLS analysis created a model that fit the data better than did QT1 analysis (Figure 2). In fact, the PLS analysis result was a nearly perfect fit to the data. However, the question arises whether the PLS analysis overfit the data by picking up all of the deviations in the samples and incorporating even unwanted noise into the model.

We also compared the results of QT1 versus PLS analysis qualitatively. In this comparison, we computed the model using PLS by adding the 89 variables in five steps, corresponding to the five groups used in the QT1 analysis. Step (1)

Table 2: Abbreviated table of design elements and samples.

Design Items	Samples 1	2	3	· · ·	47	Design items	Samples 1	2	3	· · ·	47
Large rock: no	0	1	1	· · ·	0	Azalea: no	0	0	0	· · ·	0
Large rock: 1	1	0	0	· · ·	0	Azalea: 1	1	0	0	· · ·	0
Large rock: 2	0	0	0	· · ·	0	Azalea: 2-3	0	1	0	· · ·	1
Large rock: ≥3	0	0	0	· · ·	1	Azalea: ≥4	0	0	1	· · ·	0
Middle-sized rock: No	0	0	0	· · ·	0	Pine: no	0	0	0	· · ·	0
Middle-sized rock: 1-2	0	0	0	· · ·	0	Pine: 1	1	0	1	· · ·	1
Middle-sized rock: 2–4	0	1	1	· · ·	0	Pine: ≥2	0	1	0	· · ·	0
Middle-sized rock: ≥5	1	0	0	· · ·	1	⋮	⋮	⋮	⋮	· · ·	⋮
⋮	⋮	⋮	⋮	· · ·	⋮	Bamboo fence: no	1	1	0	· · ·	1
Stone lantern: No	0	0	1	· · ·	0	Bamboo fence: short	0	0	0	· · ·	0
Stone lantern: Yukimi	0	1	0	· · ·	0	Bamboo fence: long	0	0	1	· · ·	0
Stone lantern: tall	1	0	0	· · ·	0	⋮	⋮	⋮	⋮	· · ·	⋮
⋮	⋮	⋮	⋮	· · ·	⋮	Pond: no	0	0	0	· · ·	0
Tall tree: 1	0	0	0	· · ·	0	Pond: dry	0	1	0	· · ·	1
Tall tree: 2-3	1	1	0	· · ·	1	Pond: water	1	0	1	· · ·	0
Tall tree: ≥3	0	0	1	· · ·	0	⋮	⋮	⋮	⋮	· · ·	⋮
Middle-sized tree: 1–3	0	1	1	· · ·	0	Japanese style	1	1	1	· · ·	1
Middle-sized tree: ≥4	1	0	0	· · ·	1	Western style	0	0	0	· · ·	0
⋮	⋮	⋮	⋮	· · ·	⋮	Mixed style	0	0	0	· · ·	0
						Kansei value "healing"	3.6	3.1	3.2		3.2

used 22 of the variables, step (2) used 22 + 9 = 31 variables, step (3) used 31 + 18 = 49 variables, step (4) used 49 + 28 = 77 variables, and step (5) used 77 + 12 = 89 variables. The number of latent variables used at each step was four at steps (1) and (2) and six at steps (3), (4), and (5). These numbers were found to yield the smallest residuals in several trials with different numbers of latent variables. Then, we surveyed how the ranking of categories in each item accorded with that determined by QT1. Figure 3 shows the percent accordance versus the number of variables.

When the number of exploratory variables exceed the sample size, the accordance slightly decreased (right side of the Figure 3). It seems that in the cases of smaller sample size, averaging effect is less, then small deviations reflected in the result. Overall evaluation of the PLS result is rather good; nearly 80% of the PLS results were in accordance with the QT1 results.

Using PLS analysis, one can obtain a numerically accurate model of the relationships between design elements and Kansei. In other words, the PLS result reflected smaller deviations (noise) from the sample, as reflected in the near-perfect fit to the data. Although PLS is promising, it is important to evaluate whether the result accurately reflects the consumer trend or is skewed by a particular sample.

One example of Kansei engineering result is as follows. Input of the Kansei word "curative" yields the result that the garden should have no single large free-standing stone, it should have more than six medium-sized stones arranged nonlinearly, there should be six to 10 small stones and stepping stones, and the garden type should be modern Japanese, with one pine tree and a tall stone lantern. Using PLS, we could incorporate all of the exploratory variables into the model without having to divide them into groups. Thus, we conclude that PLS analysis permits the building of a Kansei database having a large number of design elements.

6. A Hand-Made Kansei Engineering VR System

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

Three difficulties must be overcome to create and use a VR system for Kansei engineering: dynamic composition, mobility, and price. VR systems commonly display data from

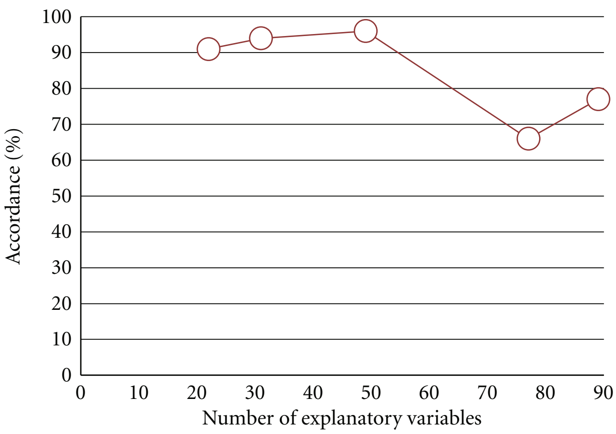


Figure 3: Accordance with PLS and QT1.

a scene that is already composed. A Kansei engineering system, on the other hand, must compose a scene dynamically from scene parts, along with the results of certain inference rules. To show the optimal design candidate for the intended Kansei, details of the design must be selected from a database of scene parts, which must then be composed into a concrete design. Thus, the Kansei VR system must have a dynamic composition function. A second requirement of a Kansei engineering system is mobility. For public viewing of a 3D scene, large-scale systems are commonly used. However, as a Kansei VR system is often required at the site of research and development, the system hardware must be relatively small. The final requirement is price. VR systems are commonly expensive, but to popularize the use of VR with Kansei engineering, the price of the system needs to be lower.

The system we have developed is able to compose an entire scene or design product from detailed 3D parts based on the results of a Kansei analysis. It consists of a common PC, a portable screen, two home-theater projectors, and polarized glasses. Its cost is less than 500,000 yen ($5,680 USD), including the PC.

In Section 6.2, we describe a personal-garden Kansei engineering VR system based on the results of PLS analysis of a Kansei evaluation (Section 5.1). An immersive VR experience is required for garden design because one normally experiences a garden from the inside. Additionally, a client and a garden builder generally differ in their knowledge of garden design; while an experienced garden builder can imagine the actual garden resulting from the design, the client generally cannot. An immersive presentation will enable the client to visualize the garden, thereby narrowing the gap between builder and client.

6.1. Previous Attempts and Problems. Although we have studied and built various handmade 3D CG or VR systems using Java3D, Xj3D, and Max/Jitter, each language has its particular problems [47]. Java 3D includes several loader library programs that can read common 3D object-description files. The most common loader is "j3d-vrml97.jar." We encountered two problems with this loader. The first was a problem with associations between vertex and texture.

Figure 4: Early prototype system built with Java3D.

Often, outputs from the modeler programs are not properly read and rendered. This appears to be caused by a dialectal variation of VRML97 notation. Figure 4 shows an early prototype system built with Java3D. The ground and fence are textured, but other components are not. Stones and rocks appear like plastics, and some trees are improperly rendered.

A second, larger problem is a mismatching between the Kansei engineering system and the "scene-graph" structure of Java3D and VRML. A scene graph is a tree-shaped graph that shows hierarchical object relationships from the root. Both VRML97 and Java3D use a scene-graph structure. A scene graph is useful for handling the data of one composed scene. However, a Kansei engineering system must generate a scene dynamically, from the seeking result of the rule base. The optimal models for a particular Kansei have to be placed in the scene. It is theoretically possible to rebuild a scene graph each time, but this would require a great deal of computation, and the scene graph itself would consume a large amount of memory.

When X3D, the successor to VRML, appeared, we tried it with Xj3D, a loader of X3D. This also required continual rebuilding of the scene graph, and the memory problem was serious. Although we built a system, the rendering quality was poor, and the maximum possible number of polygons was low [47]. After numerous trials over several years, we abandoned the concept of a 3D system based on a scene graph and instead decided to build an original rendering engine and loader. Its aims were the ability to render a large number of polygon models (e.g., trees) and to load major 3D object files, including textures. Additionally, we aimed to implement shadows, which is indispensable for a garden representation but is virtually impossible with Java3D.

6.2. 3D Rendering Framework EXEV-J. To resolve the 3D graphic problems described in the previous section, we built an original 3D rendering framework, called the Easy eXpandable Environment for Vr on Java (EXEV-J), which does not depend on a common framework such as OpenGL and Java3D. EXEV-J is the basis of the VR portion of the Kansei engineering system developed through this research. EXEV-J was written in Java, which enables it to run on numerous operating systems and machines.

To ensure expandability and versatility, the developed system includes a loader that can read and interpret general

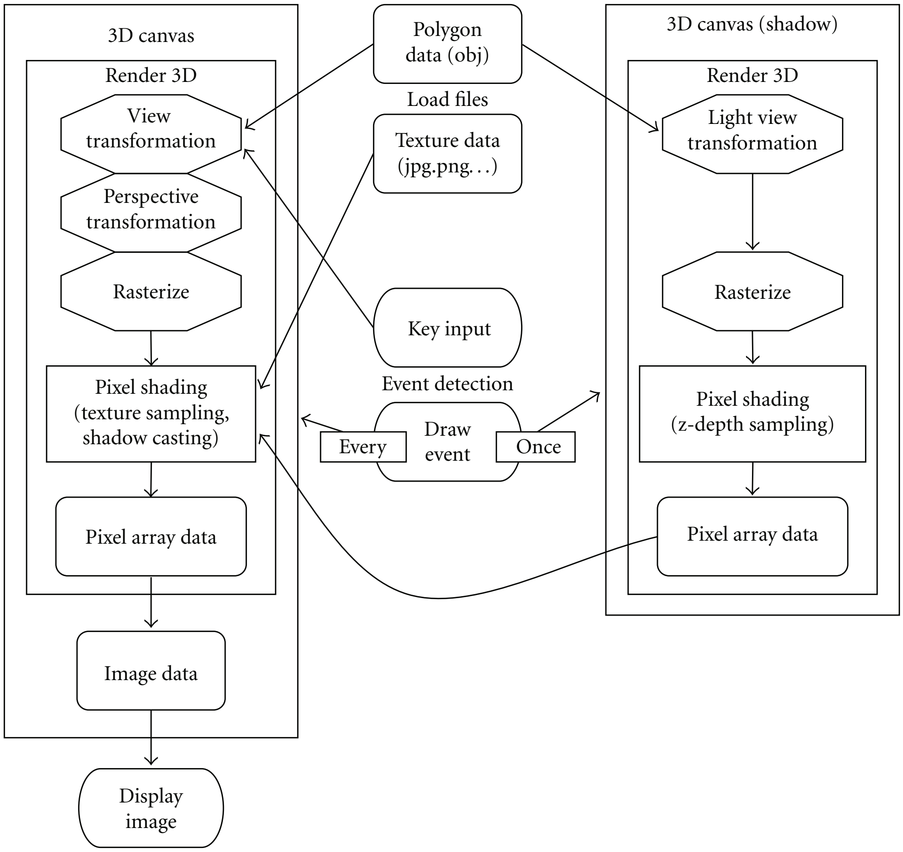


Figure 5: Original 3D framework EXEV-J.

3D object files in the OBJ format. The system includes many functions designed for 3D representation, such as transformation of polygon model coordinates (e.g., a coordinate system for local, world, viewpoint, clip, and screen), rasterization of the rendered scene, color sampling, and mapping from a texture file. Model data can be generated from common 3D CG graphics programs (e.g., 3D Studio MAX, MAYA, Blender, MetaSequoia, etc.) and saved as OBJ files.

The Canvas class, which is a basic GUI component of Java AWT graphics, was extended to include the display of rendered scenes. Thus, all of the standard GUI programming of Java can be utilized. We implemented a stereo view and scene manipulation using a mouse and keyboard. The workflow of 3D Canvas, the extended Canvas class, is shown in Figure 5.

6.2.1. Implementing Shadow. The 3D Canvas and "shadow_3D Canvas" classes are the same, except they switch transformation and memory areas. 3D Canvas does a sequence of processes: view transformation, perspective transformation, orthogonal transformation, rasterizing, and pixel shading. Shadow_3D Canvas generates shadows by orthogonal transformation and does not compute perspective transformation. Additionally, it records z-depth values of 3D images at the pixel shading stage. The z-depth buffer is refreshed at each redraw call. These values are stored in the "shadow buffer" and are shared with other routines in 3D Canvas. The size of the shadow buffer is larger than the drawing window (i.e., larger than 1600 × 1200 pixels) to generate a smooth shadow. In 3D Canvas, the shadow buffer is passed by the "call by" reference and contributes to a faster computation.

6.2.2. System Overview. The system has several databases: those having category scores, a design element table, and 3D object and texture data (Figure 6). Based on the client's choice of Kansei words, the most suitable design elements are selected. For each design item, the category with the greatest category score for that Kansei is selected. Then, from the databases, the system obtains polygon and texture data corresponding to the type(s) of trees and stone(s) selected. The polygon and texture data are then passed to 3D Canvas for the right and left eye. 3D Canvas sends the draw command to Render 3D. Then, the viewer can see a stereo view of the proposed garden design through real-time rendering. A walk-through type moving view is provided. In this implementation, we used tree models from several public-domain databases of the Google Sketchup model repository. Figure 7 shows views from several different angles of a garden design corresponding to the Kansei word "curative." Stones and other objects have textures. Figure 8 shows the effect of drop shadow from overhead and from slanted sunlight. Figure 9 shows the rendered stereo view.

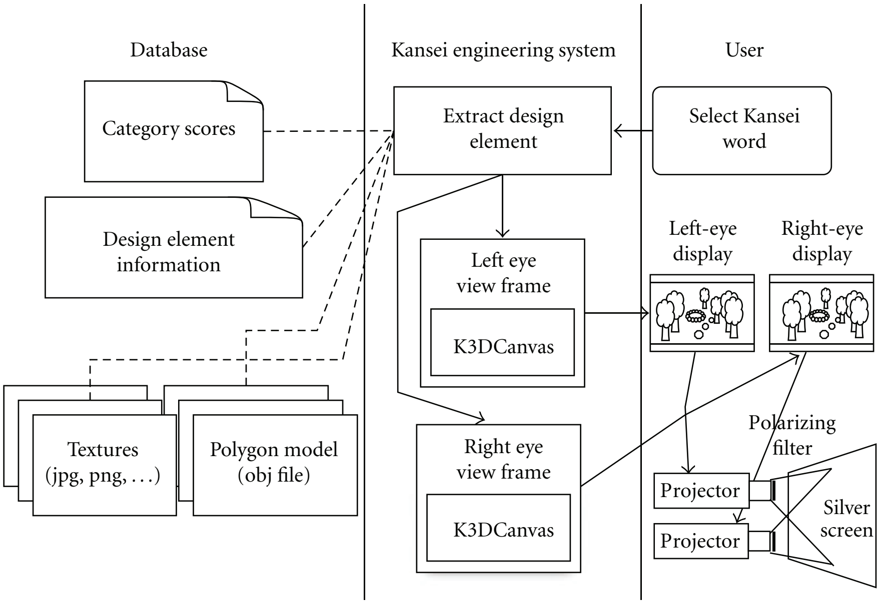


Figure 6: Scheme of hand-made Kansei VR system.

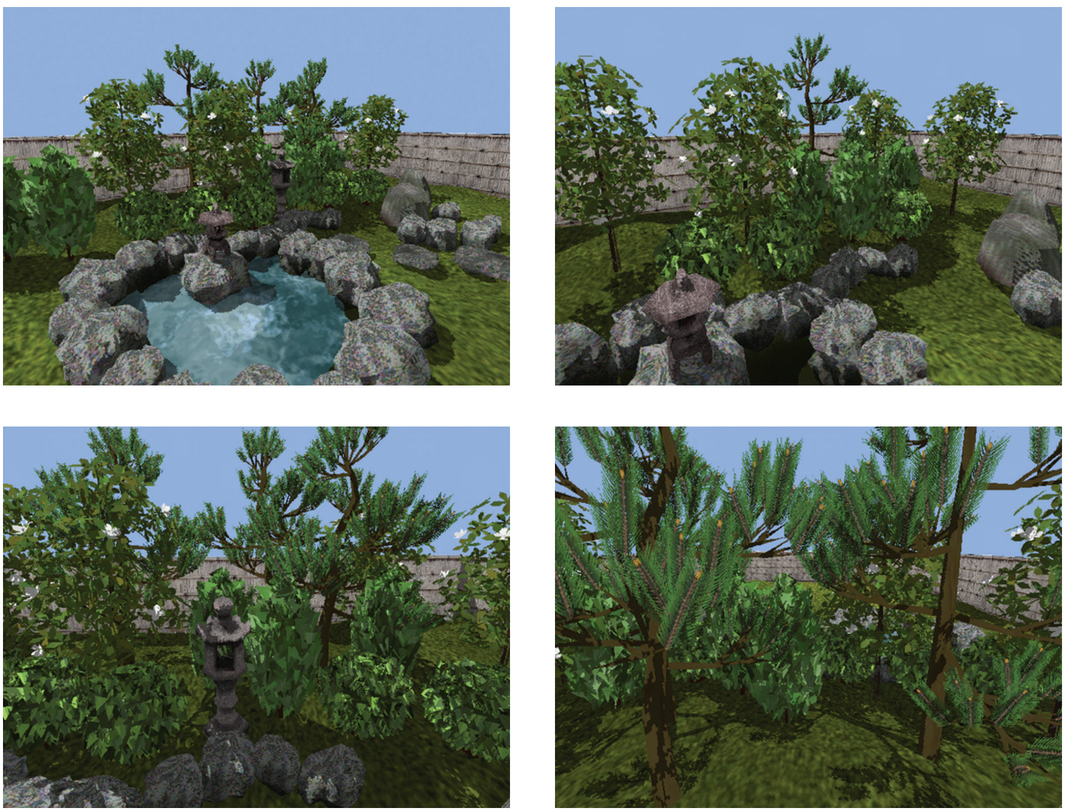
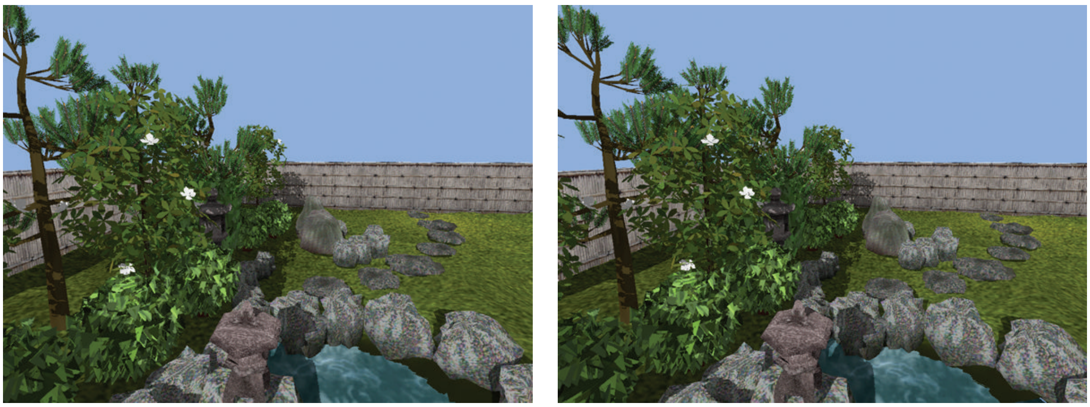


Figure 7: Entire view progressing to close up view of a rendered scene.

6.2.3. Performance Considerations. In this system, the largest composition of garden items has approximately 56,000 polygons. A typical composition has approximately 30,000 to 50,000 polygons. On a common notebook PC, the system can render a 640×480-pixel stereo view containing 50,000 polygons at 8 frames/sec or a nonstereo view at 15 frames/sec. For a scene with 30,000 polygons, the stereo view can be viewed at 13 frames/sec and the nonstereo view at 26 frames/sec. The notebook PC we used was an Apple MacBook Pro (Intel Core2 Duo 2.16 GHz, 4 GB memory, ATI

(a) (b)

Figure 8: Drop-shadow examples; (a) overhead sunlight, (b) slanting sunlight.



(a) (b)

Figure 9: Stereo view of a "curative" garden design ((a) left-eye view, (b) right-eye view).

Radeon X1600 with 128 MB VRAM). This system can also provide high-resolution rendering, such as full HD (1920 × 1080 pixels) and 2K (2048 × 1080). These high-resolution renderings are useful for disclosing details of the garden design and for preparing documents.

7. Conclusion

The aims of this study were to expand the analysis capability of Kansei and relationships among design elements using PLS and to build a Kansei VR system with the originally developed 3D computation framework.

PLS regression can incorporate all of explanatory variables, whereas QT1 has to divide them into several groups. If they are divided, the weights of explanatory variables cannot be compared, and the weight is a priority measure for explanatory variables in the Kansei database. PLS-based analysis has shown excellent results under the small sample-size situation. Utilizing PLS regression was indispensable for the Kansei analysis and building system.

A Kansei VR system for gardens was built from the analysis results using PLS. The system was built on our original 3D computation framework in Java to achieve rendering of large polygons and drop shadows. The VR system runs on a notebook PC with two projectors and a screen. Portability is good, and its price is much lower than common VR systems.

With these research results, the application of VR for Kansei engineering of complex and detailed design process could be promising.

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