Research Article

A Green-IKE Inference System Based on Grey Neural Network Model for Humanized Sustainable Feeling Assessment about Products

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Due to extraordinary concerns about the issue of environmental protection from time to time, so far, sustainable development draws much attention. In developing sustainable products, the studies on methodologies of how to precisely grasp the sustainable feeling about products and translate it into desired constructed elements are scarce. This study aims to propose a novel sustainable feeling assessment system about products, called green-initiative Kansei engineering (GIKE). The Kansei engineering scheme is a distinguished customer-oriented technology for dealing with peoples’ affection about concerning matters. In this study, we extend Kansei engineering to initially include the designated sustainable image other than statistically obtained high-ranking images. Then, through survey and analysis of concerning matters, we precisely build a GIKE inference system via the grey-model-based backpropagation neural network scheme, in which it provides a precise relationship between affective (including sustainable) images of products and their constructive elements. A computer mouse is selected as the target in experiments to verify the proposed methodology, and the result is satisfying. Through our study, we may know the way to acquire a human’s sustainable feeling about concerning matters. And, most importantly, the proposed GIKE methodology firstly and innovatively expands the application filed of Kansei engineering to the field of sustainability evaluation and translation for concerning matters.

1. Introduction

Due to quick consumption of natural resources and intensification of greenhouse effects, public awareness of greening has been continuously strengthened. Therefore, more and more researchers are beginning to investigate green problems for enterprises [1, 2]. However, so far, there lacks a proper green evaluation methodology for people to optimally estimate their subjective feeling or preferences about green sustainable matters and, moreover, translate them into physical constructed elements. In the past, a distinguished popular method, called “Kansei (Japanese word) engineering,” was firstly proposed by Nagamachi [3] in the 1980s to catch people’s feeling about living matters such as products. Kansei engineering (KE) is a customer-oriented technology for evaluating people’s affection about concerning matters. It is an inference or translating methodology of a customer’s feeling about matters to its constructed elements. This methodology has been successfully applied in many product-evaluation studies [3–9], such as cars, websites, and clothes. In dealing with product-evaluation problems using KE, the customer’s feeling or Kansei about a designated matter is collected from the marketplace. Then, a survey is conducted to build the relationship between Kansei (expressed as descriptive words) and the matter’s constructed elements. This built relationship is called a Kansei inference or evaluation system which may be used to evaluate humans’ affection about a matter from its constituent or infer the optimal design elements from humans’ affection. Despite the above-mentioned advantages of KE, KE can only be used to deal with the existed matters. For future desired or designated matters, KE is invalid.

Note that a good human’s affection inference system about existed concerning matters should be adaptive to include a new or designated (e.g., sustainable) feeling, not
limited to those collected from the questionnaire survey in conventional KE manipulation. Furthermore, the design concept of future products should be the following: based on past knowledge and experiences, designers need innovatively to catch the future trend of or even lead customers’ feeling about a product and then design a proper product to match this trend or feeling. Regarding this, we propose an initiative Kansei engineering scheme (IKE) which may not only keep the advantages of conventional KE, including the concepts of using Kansei to describe humans’ feeling and the manipulation of translating Kansei into design elements based on the information of past or existed products, but also further extend it to the area of solving future or designated-image form design problems.

Regarding the above matters, this study firstly proposes an innovative green-IKE scheme to establish a suitable human’s feeling assessment system about regarding green matters. In the green-IKE scheme, we extend KE to include the designated affective green image into statistically obtained high-level Kansei images, then analyze their corresponding constructed design elements, and eventually build a proper relationship between Kansei images (including high-level and green images) and constructed design elements via the grey-model-based backpropagation neural network scheme. The reason of adopting the grey model (GM) is that it is very powerful in dealing with sparse data [10] when usually encountered in form design problems using the KE scheme. Furthermore, the backpropagation neural network is adopted because of its strong nonlinear mapping ability [11] in establishing the relationship between product Kansei images and their constructed design elements. The introduction should be succinct, with no subheadings. Limited figures may be included only if they are truly introductory and contain no new results.

2. Proposed Methodology

2.1. Manipulation Procedure. To demonstrate the proposed innovative green-IKE methodology for green image inference or evaluation, we choose a product of computer mouse as the target matter. The manipulation procedure of the green-IKE scheme is shown in Figure 1 and has the following steps: (1) selecting a target product, i.e., the computer mouse; (2) dividing the data space into product and semantic (image) spaces; (3) finding the representatives of collected products and Kansei (affection) words, reducing data, and obtaining high-level images. In this study, we used descriptive words to describe humans’ Kansei or affection about a product; (4) incorporating the green image and its corresponding green constructed elements; (5) obtaining Kansei evaluation data via the questionnaire survey and performing some statistical calculations; (6) establishing a mathematical relationship between product images and form elements and therefore completing the Kansei assessment system; and (7) verifying the proposed green-IKE scheme or the Kansei assessment system.

In step 6, the mathematical modelling scheme of the Kansei assessment system used is the grey-model-based backpropagation neural network (GMBN). The details of the GMBN are addressed in Section 2.2.

2.2. Theory and Topology. The GMBN scheme is a combination of the grey model (GM) and backpropagation neural network (BPNN), which may be used to deal with sparse data (using GM) but still have strong mapping abilities (using BPNN), especially suitable for the problem of Kansei evaluation or prediction for the product form.

In the GM [10], firstly, the original sequence of data is accumulated once, and it is considered that these accumulated data will follow certain rules. Then, we may find a classical curve to fit these accumulated data. Assume there is an original time sequence of data \( x(0) \):

\[
\{x(t) \mid t = 1, 2, 3, \ldots, n\} = \{x_1^{(0)}, x_2^{(0)}, \ldots, x_n^{(0)}\}. \tag{1}
\]

A first accumulated addition is done to the original data sequence, and a new data sequence \( x(1) \) is obtained as

\[
x^{(1)} = \{x_t^{(1)} \mid t = 1, 2, 3, \ldots, n\} = \{x_1^{(0)} + x_2^{(0)}, x_2^{(0)} + x_3^{(0)}, \ldots, x_n^{(0)} + x_1^{(0)}\}. \tag{2}
\]

Based on the new data sequence \( x^{(1)} \), a first-order differential equation is built as

\[
\frac{dx^{(1)}}{dt} + ax^{(1)} = u. \tag{3}
\]

The solution of the above ordinary differential equation is

\[
x_t^{(1)} = \left(x_1^{(0)} - \frac{u}{a}\right)e^{-a(t-1)} + \frac{u}{a}, \tag{4}
\]

where \( x_t^{(1)} \) is the estimated value of \( x_t^{(0)} \). Then, an accumulated subtraction is done to \( x_t^{(1)} \). A final estimated value of \( x_t^{(0)} \) is obtained, which is denoted as \( x_t^{(0)} \) given by

\[
x_t^{(0)} = x_t^{(1)} - x_{t-1}^{(1)}, \quad t = 2, 3, \ldots \tag{5}
\]

For convenience, we define the following variables. The original data sequence \( x_t^{(0)} \) is denoted as \( \eta(t) \), the first accumulated data sequence \( x_t^{(1)} \) as \( \xi(t) \), and the predicted data sequence \( x_t^{(2)} \) as \( \varphi(t) \).

In this study, we have a total of four dependent variables of Kansei words (\( Y_1, Y_2, Y_3 \), and \( Y_4 \)) and twelve independent variables of form design elements (\( X_1 \sim X_{12} \)). For each dependent variable (e.g., \( Y_1 \)) and its corresponding independent variables (\( X_1 \sim X_{12} \)), we may construct a first-order differential equation as

\[
\frac{d\xi_1}{dt} + a\xi_1 = b_1\xi_2 + b_2\xi_3 + \cdots + b_{12}\xi_{13}, \tag{6}
\]

where \( \xi_1 \) may be \( Y_1, Y_2, Y_3, \) or \( Y_4 \) and \( \xi_2 = X_1, \xi_3 = X_2, \ldots, \xi_{13} = X_{12} \). The time-response solution of the above equation can be obtained as
$$\xi_1^*(t) = \left((\xi_1(0) - d) - \xi_1(0) \cdot \frac{1}{1 + e^{-at}} + 2d \cdot \frac{1}{1 + e^{-at}}\right) \cdot (1 + e^{-at}),$$  
(7)

$$d = \frac{b_1}{a} \xi_2^*(t) + \frac{b_2}{a} \xi_3^*(t) + \ldots + \frac{b_{12}}{a} \xi_{13}^*,$$  
(8)

Equations (7) and (8) can be converted into a backpropagation neural network [11] to form a GMBN with \( n \) inputs and one output. The topology of this GMBN is shown in Figure 2. There are a total of four layers in the GMBN, named LA, LB, LC, and LD. The input parameters are set as \( \xi_2(t), \xi_3(t), \ldots, \xi_n(t), n = 13 \). The connecting network weight is expressed as follows: \( \omega_{11} = a \) between LA and LB; \( \omega_{21} = -y_1(0), \omega_{22} = 2b_1/a, \omega_{23} = 2b_2/a, \ldots, \) and \( \omega_{2n} = 2b_{n-1}/a \) between LB and LC; and \( \omega_{31} = \omega_{32} = \ldots = \omega_{3n} = 1 + e^{-at} \) between LC and LD. The threshold value of layer LD is

$$\phi(t) = \left(1 + e^{-at}\right)(d - y_1(0)).$$  
(9)

The operational relationship between the input and the output for each neuron in every layer is defined as follows:

- In layer LA with one neuron: \( A = \omega_{11} t \).
- In layer LB with one neuron: \( B = f(\omega_{11} t) = 1/1 + e^{-\omega_{11} t} \).

In layer LC with thirteen neurons: \( C_1 = B\omega_{21}, \)

\( C_2 = \xi_3(t)B\omega_{22}, \ldots, C_{11} = \xi_n(t)B\omega_{211} \).

In layer LD with one neuron: \( D = \omega_{31} C_1 + \omega_{32} C_2 + \ldots + \omega_{3n} C_n - \phi(t) \).

The total error is calculated as the difference between the network output and the expected value:

$$\delta = D - y_1(t).$$  
(10)

And, according to the error of \( \delta \), the weight and threshold values of the network may be adjusted till convergence.

### 3. Results and Discussion

#### 3.1. Experiment

The experiments of this study involve 120 subjects which are divided into three teams. The first team has 40 members, including 25 males and 15 females. Each member has more than 5 years’ experience of using electronic mouse products. The mission of the members of the first team is to extract the sample representatives. The second team has 40 members, including 25 males and 15 females. Each member is a professional designer with more than 5 years’ experience of designing 3C devices. The mission of the second team is to perform the morphological analysis of mouse products. The third team has 40 members, including 25 males and 15 females. Each member has more than 5 years’ experience of ever buying electronic mouse products.
3.2. Product Sample Collection and Reduction. Firstly, we selected 90 computer mouses of different models and makers in the marketplace, which entered the market during 2013–2018. Aggregately, sixty different styles of mouses, excluding those used for specific purposes or of too exaggerated appearances, were chosen to construct the product space. These mouse samples were presented in pictures in the manner as similar as possible in contrast and size and simple to be comparable in experiments. Afterward, we asked the 40 subjects of the first team to classify these 60 extracted mouse samples into 2∼10 groups based on their similarity degrees making use of the Kawakida Jirou method [12]. A similarity matrix was built and transformed into a dissimilarity matrix, and after that, it was analyzed by the multidimensional scaling (MDS) scheme. Through calculation, a result of 5 dimensions was obtained, which has a stress of 0.04782 under the suggested value of 0.05 [13]. Furthermore, we used the K-means clustering method to obtain the representative of each group. The obtained results of the first group are shown in Table 1.

The form design elements were determined by the second team, which were style, color, material, and technology. Meanwhile, a morphological analysis was performed by the second team as well to extract the form features from the samples of 5 groups, and the results are listed in Table 2. It is seen from this table that there appear totally 9 different types of form elements, denoted as $X_1$∼$X_9$, which are $X_1$: whole figure, $X_2$: upper face, $X_3$: lateral face, $X_4$: color type, $X_5$: number of colors, $X_6$: surface material, $X_7$: texture, $X_8$: light, and $X_9$: totem. Each form design element has two to three different types, depending on its complexity.

3.3. Product Image Collection and Refinement. Here, as the usual manipulation way in KE, we used adjective words to describe the customer’s psychological feeling and perception (Kansei, a Japanese word) about the appearance of a product. Aggregately, sixty descriptive words or Kansei words describing the integral feeling of mouse samples were collected from newspapers, magazines, journals, literature, articles, websites, and customers. After omitting the absurd, resembling, or too exaggerate words, we finally got 20 medium-level Kansei words. Then, a Kansei questionnaire interview was done to the subjects of the second team. The obtained interview results were further refined via factor analysis. Eventually, three high-level Kansei words are obtained and shown in Table 3, which are fashionable ($Y_1$), technological ($Y_2$), and ergonomic ($Y_3$).

3.4. Initiative Green Image and Form Elements. From the professional opinions about the green mouse products of the second team members, it is suggested to add three green form elements, $X_{10}$: green color or light, $X_{11}$: green image, and $X_{12}$: green material, as shown in Table 3. On the contrary, the green Kansei image is simply selected as $Y_4$: green. Eventually, for the chosen target computer mouse, we may construct four Kansei images ($Y_1$∼$Y_4$) and twelve form elements ($X_1$∼$X_{12}$).

3.5. Kansei Evaluation: Model Building and Verification. A questionnaire survey, using a 7-scale semantic differential scheme, was done to 40 subjects of the third team for evaluating their preferences about the 60 extracted mouse samples and 10 newly designed green mouse samples (named the second group) which were designed by professional product designers. The obtained average scores of $Y_1$∼$Y_4$ for all samples are listed in Table 4. Among the extracted 60 samples, we randomly chose 45 samples for training and 15 samples for testing. Furthermore, among the 10 testing green-designed samples, we randomly...
### Table 1: Samples of group 1 and its representatives.

| Sample    | Distance |
|-----------|----------|
| No. 1     | 0.723    |
| No. 2     | 0.767    |
| No. 3     | 0.883    |
| No. 4     | 0.917    |
| No. 5     | 0.921    |
| No. 6     | 0.814    |
| No. 7     | 0.788    |
| No. 8     | 0.728    |
| No. 9     | 0.763    |
| No. 10    | 0.823    |
| No. 11    | 0.811    |
| No. 12    | 0.765    |
| No. 13    | 0.692    |
| No. 14    | 0.701    |

Representative (No. 13)
chose 7 samples for training and 3 samples for testing. In summary, we had 52 product samples for training and 18 samples for testing. Besides, we used the scheme of genetic algorithm [14] to avoid the restraint of local extreme values and enhance the convergence speed of error. Afterward, based on the above concerns, we trained the genetic-algorithm-optimized GMBN topology by using previously assigned 52 training samples with data pair \((X_1 \sim X_{12}, Y_i)\). It takes 32, 28, 20, and 36 iterations to train the GMBN for the target \(Y_1, Y_2, Y_3,\) and \(Y_4,\) respectively, to reach the criterion of error

| Attribute          | Design element | Types                          |
|--------------------|----------------|--------------------------------|
| Style              | \(X_1:\) whole figure | Rectangle, triangle, cylinder |
|                    | \(X_2:\) upper face   | Flat, arc, multiple           |
|                    | \(X_3:\) lateral face  | Flat, indent, multiple        |
| Color              | \(X_4:\) color type   | Cold, medium, warm            |
|                    | \(X_5:\) number of colors | One, two, multiple           |
| Material           | \(X_6:\) surface material | Plastic, wood, compound |
|                    | \(X_7:\) texture       | Smooth, rough, multiple       |
| Technology         | \(X_8:\) light         | No, with LED light            |
|                    | \(X_9:\) totem          | No, with totem                |
| Green              | \(X_{10,:}\) green color/light | No, with green color or light |
|                    | \(X_{11,:}\) green image | No, with bionic shape         |
|                    | \(X_{12,:}\) green material | No, with biodegradable material |

Table 2: Morphological analysis results of product samples.

| Attribute | Design element | Types |
|-----------|----------------|-------|
| Style     | \(X_1:\) whole figure | Rectangle, triangle, cylinder |
|           | \(X_2:\) upper face   | Flat, arc, multiple           |
|           | \(X_3:\) lateral face  | Flat, indent, multiple        |
| Color     | \(X_4:\) color type   | Cold, medium, warm            |
|           | \(X_5:\) number of colors | One, two, multiple           |
| Material  | \(X_6:\) surface material | Plastic, wood, compound |
|           | \(X_7:\) texture       | Smooth, rough, multiple       |
| Technology| \(X_8:\) light         | No, with LED light            |
|           | \(X_9:\) totem          | No, with totem                |
| Green     | \(X_{10,:}\) green color/light | No, with green color or light |
|           | \(X_{11,:}\) green image | No, with bionic shape         |
|           | \(X_{12,:}\) green material | No, with biodegradable material |

Table 3: FA results: accumulated contribution of the factor group.

Table 4: Kansei evaluation results of extracted samples.
convergence (root-mean-square error (RMSE) less than or equal to 0.005). The RMSE is defined as

\[
\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{m} (\hat{Y}_t - Y_t)^2}{m}},
\]

where \( m \) is the sample number, \( \hat{Y} \) is the value of the Kansei-word score obtained by the experiment, and \( Y \) is the predicted Kansei-word score.

The training process for \( Y_1 \) with 32 iterations to reach convergence is shown in Figure 3. The obtained maximal errors (relative errors) between predicted and measured high-level Kansei images of \( Y_1, Y_2, Y_3, \) and \( Y_4 \) are 0.0996 (1.988\%), 0.0872 (1.45\%), 0.0889 (2.31\%), and 0.0922 (3.15\%), respectively. Specifically, the result of error between predicted and measured \( Y_1 \) is shown in Figure 4. It is inspiring that the training results of \( Y_1 \sim Y_4 \) are excellent.

On the contrary, to verify the trained results, we adopted the previously assigned 18 testing samples. Using the already constructed GMBN topology, the obtained relative errors between predicted and measured high-level Kansei images of \( Y_1, Y_2, Y_3, \) and \( Y_4 \) are 2.71\%, 3.18\%, 2.16\%, and 3.44\%, respectively. Specifically, the verification result in terms of the comparison between predicted and measured \( Y_1 \) (maximal error 0.1423, relative error 2.71\%) is shown in Figure 5. Overall, the verification results are satisfying.
4. Conclusion

In this study, we have innovatively developed a methodology of green-IKE with the genetic-algorithm-optimized GMBN as its mapping model for product form evaluation and prediction. This novel scheme is an extension of traditional Kansei engineering which is not able to handle problems of product form design with future or predetermined images. Specifically, the proposed green-IKE scheme subjectively adds the green image of the product and its green form elements to the obtained high-level Kansei images and form elements, respectively, in KE manipulations. The verification results show that this green-IKE scheme performs well in dealing with the Kansei evaluation of electronic mouse products. Through the operation of the green-IKE, designers may easily understand or further catch the idea of how to properly design the related form elements to fit the green image of electronic mouse products. It is very easy to generalize the proposed green-IKE scheme to other product assessment problems like electronic appliances or living products.

Data Availability

Related data are available from the corresponding author once this paper is accepted and published.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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