Constructing a Hybrid Kansei Engineering System Based on Multiple Affective Responses: Application to Product Form Design

Chih-Chieh Yang
Department of Multimedia and Entertainment Science, Southern Taiwan University,
No. 1, Nantai Street, Yongkang District, Tainan City 71005, Taiwan, ROC

Abstract
This study proposes an expert system, which is called hybrid Kansei engineering system (HKES) based on multiple affective responses (MARs), to facilitate the development of product form design. HKES is consists of two sub-systems, namely forward Kansei engineering system (FKES) and backward Kansei engineering system (BKES). FKES is utilized to generate product alternatives and BKES is utilized to predict affective response of new product designs. Although the idea of HKES and similar hybrid systems have already been applied in various fields, such as product design, engineering design, and system optimization etc., most of existing methodologies are limited by searching optimal design solutions using single-objective optimization (SOO), instead of multi-objective optimization (MOO). Hence the applicability of HKES is limited while adapting to real-world problems, such as product form design discussed in this paper. To overcome this shortcoming, this study integrates the methodologies of support vector regression (SVR) and multi-objective genetic algorithm (MOGA) into the scheme of HEKS. BKES was constructed by training SVR prediction model of every single affective response (SAR). The form features of these product samples were treated as input data while the average utility scores obtained from all the consumers were used as output values. FKES generates optimal design alternatives using the MOGA-based searching method according to MARs specified by a product designer as the system supervisor. A case study of mobile phone design was given to demonstrate the analysis results. The proposed HKES based on MARs can be applied to a wide variety of product design problems, as well as other MOO problems involving with subjective human perceptions.

Keywords: Product form design; Kansei engineering; Support vector regression; Multi-objective genetic algorithm.

1. Introduction
The way that a product looks is one of the most important factors affecting a consumer’s purchasing decision. The task of an industrial designer is to manipulate product attributes (PAs), in this way, to produce specific styles which satisfy the consumer’s expectations. Traditionally, the success of a product’s design depended on the designers’ artistic sensibilities, which quite often did not meet with great acceptance in the marketplace. Therefore, many product design studies have been carried out to get a better insight into consumers’ subjective perceptions. The most notable research is Kansei engineering (KE). KE is originated from Japan in 1970’s and not aware by the product design community until the journal papers published by Mitsuo Nagamachi and his colleges (Jindo et al., 1995; Nagamachi, 1995). The basic assumption of KE studies is that there exists a cause-and-effect relationship between affective responses (ARs) and a product’s attributes. However, their research has several limitations and thus impairs the development of real-world applications for product design.

As an interesting application of product design, the concept of hybrid Kansei engineering system (HKES) was first proposed by Matsubara & Nagamachi (1997), which aim at generating product design according to consumers’ ARs. Since subjective human feelings are often very complex and might be conflicting with each other, product design system based on single affective response (SAR) of consumers can not generate suitable product alternatives while considering multiple affective responses (MARs) simultaneously. Until now, very few studies of HKES have emerged in the literature. Among the existing studies, the works of Hung-Cheng Tsai have been successfully applied HKES to product form design (Hsiao & Tsai, 2005) and product color planning (Tsai & Chou, 2007). In their studies, genetic-based product alternative searching according to MARs is treated as a single-objective optimization (SOO) problem which minimizes the normalized weighted error of different ARs. According to the best of the author’s knowledge, all previous studies of HKES in the field of product design are restricted to use SOO. The only exception to this trend is the recent work of Hong et al. (2007). However, their methodology was combined with multiple linear regression (MLR) models and an optimization technique of steepest descent, which may not have a satisfactory result due to the poor predictive performance of the linear models. In other fields besides that of product design, some methodologies similar to HKES can be found. One of them is the research of interactive evolutionary computation (IEC) (Takagi, 2001). IEC is an optimization method which uses evolutionary computation (EC) for system optimization based on subjective human evaluation. The approximation of the fitness values using neural networks (NN) is the most frequently used technique to obtain faster convergence of IEC. Despite of the motivation to adopt such hybrid scheme, the
applications of HKES and IEC both seek to construct a relationship, between the psychological space of human evaluation and the attribute space of the specified objects, which is often difficult or impossible to define. Some research of engineering design can also be found to adapt such hybrid scheme for solving optimization problems without explicitly known forms of objective functions (Wang, 2005; Liang & Huang, 2007; Yuan et al., 2007).

In the author’s previous studies, state-of-the-art machine learning approaches known as support vector machine (SVM) (Shieh & Yang, 2008a) and support vector regression (SVR) (Yang & Shieh, 2010) were introduced to develop a model that predicts consumers’ ARs for product form design with a very satisfactory predictive performance. The product form features were analyzed by a morphological analysis (Jones, 1992), which results in a product form representation with a mixed of continuous and discrete design attributes. The relative importance of the form features can also be identified by a feature selection method (Shieh & Yang, 2008b). As a follow-up research, this study proposes HKES based on MARs using SVR and multi-objective genetic algorithm (MOGA) for product form design. Basic product form samples were prepared for gathering ARs of consumers. The form features used as input data and the AR scores gathered from the questionnaire as output values were used to construct the SVR prediction models. The optimal parameters of the SVR models were determined by five-fold cross-validation (5FCV). Finally, the MOGA-based searching model can generate product form design alternatives according to the predictive MAR output values of SVR models. The reminder of the paper is organized as follows: Section 2 reviews the background of HKES, nonlinear prediction model for ARs, and heuristic searching algorithms. Section 3 presents the outline of the proposed HKES for product form design. The detailed implementation procedures of the proposed method are given in Section 4. Section 5 demonstrates the experimental results using mobile phone designs as an example. Section 6 presents some brief conclusions.

2. Background review

2.1. Hybrid Kansei engineering system

HKES is in fact a kind of expert system for product design which can be used to model the needs of consumers and facilitate the industrial designers to develop product designs more efficiently. A typical scheme of HKES is shown in Fig. 1. HKES is consists of two sub-systems, namely forward Kansei engineering system (FKES) and backward Kansei engineering system (BKES). In general, FKES is
utilized to generate product alternatives and BKES is utilized to predict the ARs of new product designs. Obviously, the nub of HKES is how to construct the nonlinear models with high predictive ability and to use a robust searching algorithm to generate new product designs. Another important characteristic is that FKES can not work without BKES. More specifically, the searching algorithm will generate the combination of features and needs the prediction model in BKES to evaluate the predictive AR values. It can be observed that the studies such as Hsiao & Liu (2004); Hsiao & Tsai (2005); Tsai & Chou (2007) follow the similar scheme proposed by Nagamachi (1995) regardless of the detailed implementations. However, the author’s interpretation of HKES is slightly different from the original concept of Nagamachi (1995). In their ideas, FKES is used to search product alternatives which satisfying the consumer’s preference while BKES is used for the designer to evaluate the product alternatives. Since the predictive ability of BKES relies on the AR data gather from the subjects (consumers or designers) to evaluate the collected product samples, the applications of BKES not only can be used to predict the designers’ intents but is also very useful for modeling AR of consumers. The optimized product alternatives obtained by FKES depend on whether the AR data of the consumers or the designers is used.

< Insert Fig. 1 about here >

2.2. Nonlinear prediction model for affective responses

The most critical problem to construct HKES, as mentioned in previous section, is how to deal with the nonlinear relationship between PAs and ARs. There exist various methods which can be used to construct the prediction model in BKES, regarding it as a regression/function estimation problem. The mostly adopted techniques in the product design field such as MLR (Han et al., 2004), quantification theory type I (QT1) (Jindo et al., 1995), partial least squares regression (PLSR) (MacKay, 2006) are heavily dependent on the assumption of linearity hence can not deal with the nonlinear relationship effectively. In addition, prior to establish the prediction model, data simplification or variable screening is often needed to obtain better results.

To deal with the nonlinearity of many-to-many mapping between variables, NN is a good candidate for building such a prediction model. A few researches have illustrated the use of NN in the product design field. Hsiao & Huang (2002) demonstrated the ability of NN to deal with the nonlinear relationships between the form features. In a later research of Hsiao & Tsai (2005), NN was used as part of a
hybrid framework for a product form search. However, NN suffers from a number of shortcomings. NN is considered a “black-box” necessitating numerous control parameters and it is difficult to obtain a stable solution. Vapnik (1995) developed a new kind of NN algorithm called SVM. SVM has been shown to provide better performance than traditional learning techniques (Burges, 1998). SVM is also known for its elegance in solving nonlinear problems using the kernel trick, which automatically carries out a nonlinear mapping to a feature space. With the introduction of appropriate loss function, SVM can be extended to solve function estimation problems, which is known as SVR. Despite being endowed with a number of attractive properties, SVM and SVR have yet to be applied widely in the field of product design except for the studies of Shieh & Yang (2008a) and Yang & Shieh (2010).

2.3. Automatic product design using heuristic searching algorithms

Automatic product design can be regarded as a process for inducing product alternatives which are satisfied with certain criteria. Implemented in HKES, it is carried out by the searching algorithm embedded in FKES. Although genetic algorithm (GA) is the most frequently-used method for the purpose of automatic product design, there are other methods such as genetic programming (GP) (Hewgill & Ross, 2004), particle swarm optimization (PSO) (Tsafarakis et al.), and ant colony optimization (ACO) (Albritton & McMullen, 2007) which are also very potential used as the searching algorithm in FKES. It is known that to obtain the optimized product alternatives in FKES is an NP-hard problem and adopting these heuristic techniques in FKES can avoid exhaustive evaluation of all possible permutations of PAs. Note that the product alternatives need to have well-defined structure and combination rules of PAs. This is also the main reason why the morphological analysis is used to decompose product samples into several main components and examining every possible attribute for each component.

Like many real-world design problems are concerned with multiple criteria or objectives which might be conflicting to each other, HKES based on SAR degrades its practical use. Therefore, the searching algorithm adapted in FKES should be in the form of multi-objective searching. Compared to classical methods such as weighted metric methods and goal programming, evolutionary algorithms (EAs) are more suitable to deal with the multi-objective optimization problem (MOP) (Deb, 2001). The novelty of EA for solving MOP lies in its capability to simultaneously preserve a diverse set of multiple non-dominated (equally good) solutions, instead of a single optimal solution. The iteration process can converge close to the Pareto-optimal front.
and with a good spread instead of a single solution like in classical methods. In a consequence, MOGA, as a kind of EA for MOP, is adapted as the searching algorithm of product form design according to the MARs of consumers.

3. Outline of the proposed HKES for product form design

In this study, HKES based on MARs is proposed to generate product form design automatically. An overview of the proposed model is shown in Fig. 2. First, in BKES, PAs $x_1, \ldots, x_m$ of $p$ collected product samples $X$ and the AR data evaluated by consumers were used to train the prediction models of SVRs. For the application of product form design in this study, the PAs denote the form features of a product. The proposed model of HKES can be implemented to product form design by defining suitable structure of form elements. The prediction models of MARs $y_1, \ldots, y_n$ are consists of $n$ individual SVR models of every SAR. Second, in FKES, according to the input MARs queried by the designer, the MOGA-based searching algorithm was used to generate product alternatives iteratively. In each iterative step, the combination of PAs $x'_1, \ldots, x'_n$ generated by the MOGA algorithm is evaluated by the prediction models in BKES. The resulting predictive MARs $y'_1, \ldots, y'_n$ obtained from BKES are used to sort the population of product alternatives on the basis of non-domination. In such way, a set of Pareto-optimal front product alternatives which satisfied with the input MARs can be obtained. The detailed implementation procedures of the proposed HKES for product form design are detailed in the following section.

< Insert Fig. 2 about here >

4. Implementation procedures

4.1. Preparation of basic product form samples

A total of 69 mobile phones of different design were collected from the Taiwan marketplace. In this aspect of form representation for product design, this study adopted morphological analysis (Jones, 1992). In fact, morphological analysis is the most widely used technique in the studies of KE due to its simple and intuitive way to define product form features. The mixture of continuous and discrete attributes is also allowed. This method begins with decomposing the product into several main components then examining every possible attribute for each component. For this study, a mobile phone was decomposed into body, function button, number button and
Continuous attributes such as length and volume are recorded directly. Discrete attributes such as type of body, style of button etc. were represented as categorical choices. Twelve form features of the mobile phone designs, including four continuous attributes and eight discrete attributes, were used. Continuous attributes were normalized to the range [0, 1]. The discrete attributes, which are in fact nominal variables, were pre-processed using one-of-n encoding. Taking a three-category attribute “circle, rectangle, triangle” for example, it can be represented as (0, 0, 1), (0, 1, 0), and (1, 0, 0). A complete list of all form features is shown in Table 1. Notice that the color and texture information of the product samples were ignored and were emphasized on the form features only. The images of product samples used in the experiments were converted to gray image using image-processing software.

< Inset Table 1 about here >

### 4.2. Semantic differential evaluation for affective responses

Three pairwise adjectives including traditional-modern, heavy-handly and rational-emotional were used for semantic differential (SD) evaluations (Osgood et al., 1957). To collect subjects’ evaluation data for the basic product samples, 30 subjects (15 of each sex) were asked to evaluate product samples using a score from -1 to +1 in an interval of 0.1. In this manner, consumers can express their subjective perception toward every product sample by choosing one of the pairwise adjectives. Take the paired adjectives “traditional-modern” for example. If a consumer evaluates a certain product sample with a score of +1.0, it means this product suggests a strong ‘modern’ feeling to the consumer. And vice versa; if a score of –1.0 is evaluated, this product projects a strong ‘traditional’ feeling. A zero value indicates that the consumer perceived a neutral feeling between the modern and traditional. It should be mentioned that if consumers are asked to evaluate the whole set of product samples at the same time, the experimental results would inevitably produce more errors. As a consequence, each consumer was asked to evaluate only 23 product samples (one-third of the total) randomly picked from all the samples. The product samples were presented to consumers in the format of questionnaires by asking them the SD scores of the adjectives. In order to collect the evaluation data in a more effective way, a user-friendly interface for the questionnaire was also provided, as shown in Fig. 3. The evaluation data of each subject can be recorded directly, thus simplifying the data post-processing time. The presentation orders of the products were randomized to avoid any systematic effects. All the subjects’ evaluation scores toward each product sample were averaged to reach a final utility score. These scores were applied as the
4.3. Constructing the support vector regression prediction model

SVR was used to construct the prediction model based on the collected product samples. The form features of these product samples were treated as input data while the average utility scores obtained from all the consumers were used as output values. Since SVR can only deal with one output value at a time, three prediction models were constructed and accorded different adjectives. The training scheme of a single prediction model based on SVR is depicted in Fig. 4. First, input product samples consisting of a series of the form features are fed into the training model. These input samples are mapped into feature space by the map function \( \phi \). Then, using the kernel function, dot products are computed with the images of the training samples under the map \( \phi \). The weights in SVR represent the knowledge acquired from the product samples. Finally, the dot products are added up using the weights. This, plus the constant term \( b \), yields the final predictive output value. The process described here is very similar to the regression in NN, only in the case of SVR the weights in the input layer are a subset of the training samples. Of the commonly used kernel functions, the Gaussian kernel is favored for many applications due to its good features (Wang et al., 2003); and thus was adapted as follows:

\[
K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right),
\]

where \( \sigma \) is the spread parameter determining the influence of squared distance between \( x_i \) and \( x_j \) to the kernel value. Since the number of product samples is limited, it is important to obtain best generalization performance and reduce the overfitting problem. In order to obtain optimal SVR training model, 5FCV is used to search best combination of parameters, including the regularization parameter \( C \), the parameter \( \varepsilon \) of the \( \varepsilon \)-insensitive loss function, and the spread parameter \( \sigma \) of Gaussian kernel. Since the process of cross-validation is very time-consuming, a two-step strategy is taken to find the optimal parameters. In the first step, a coarse grid search is taken using the following sets of values: \( C = \{10^{-5}, 10^{-4}, ..., 10^5\} \), \( \varepsilon = \{10^{-5}, 10^{-4}, ..., 10^5\} \), \( \sigma^2 = \{10^{-5}, 10^{-4}, ..., 10^5\} \). Thus \( 11 \times 11 \times 11 = 1331 \) combinations of parameters are tried in this step. An optimal \((C_0, \varepsilon_0, \sigma_0^2)\) is selected.
from the coarse grid search. In the second step, a fine grid search was conducted around \((C_0, \varepsilon_0, \sigma_0^2)\), where
\[
C = \{0.2C_0, 0.4C_0, ..., 0.8C_0, 2C_0, 4C_0, ..., 8C_0\},
\]
\[
\varepsilon = \{0.2\varepsilon_0, 0.4\varepsilon_0, ..., 0.8\varepsilon_0, 2\varepsilon_0, 4\varepsilon_0, ..., 8\varepsilon_0\},
\]
and
\[
\sigma^2 = \{0.2\sigma_0^2, 0.4\sigma_0^2, ..., 0.8\sigma_0^2, 2\sigma_0^2, 4\sigma_0^2, ..., 8\sigma_0^2\}.
\]
A total of \(9 \times 9 \times 9 = 729\) combinations are tried in this step. The final optimal parameters were selected from this more detailed search. The root mean squared error (RMSE) was used to evaluate the performance of training models using different parameters. The RMSE is defined as follows:
\[
RMSE = \sqrt{\frac{1}{l} \sum_{i=1}^{l} (y_i - d_i)^2}
\]
where \(y_i\) and \(d_i\) denote the predicted output and the measured value respectively of \(l\) product samples. The best combination of parameters of each SVR model was chosen to build the prediction model using all product samples.

< Insert Fig. 4 about here >

4.4. Implementation of MOGA-based product form searching

For the purpose of MOGA-based product form searching, this study adopts an elitist non-dominated sorting genetic algorithm (termed NSGA-II), which is popular for solving MOP in a wide variety of applications. Compared to the original NSGA, NSGA-II is more computationally efficient. More specifically, NSGA-II uses a specialized designed tournament selection operator, which is based on the crowding distance to measure how close a chromosome to its neighbors, to preserve the diversity in the population without specifying any additional parameters (NSGA uses fitness sharing). For the complete description of NSGA-II the author refer to Deb et al. (2002).

According to the input MAR values (e.g. traditional-modern, heavy-handly and rational-emotional), which is specified by a designer, NSGA-II is capable to obtain the Pareto front product alternatives. Each product sample is represented as a twelve-attribute chromosome (four continuous attributes and eight discrete attributes). The optimization procedure of NSGA-II starts with randomly generating an initial population of chromosomes, within the range of the form features. The form feature values are constrained by lower and upper bonds. That is, continuous attributes are within the range \([0, 1]\). The discrete attributes, which is represented in the form of
integer, were bounded in the range of \([1, q]\), where \(q\) is the number of the categorical choices in each attribute. Therefore, NSGA-II only needs to handle box constraint by sampling within the intervals. Each chromosome of the population is assigned the fitness values calculated from the SVR prediction models for each of the three affective dimensions. During each generation, the better chromosomes in the parent population, the “elites”, will be selected by using crowding tournament selection operator. Same as traditional GA, the selected chromosomes will then go through crossover and mutation operations to form the offspring population. The simulated binary crossover (SBX) (Deb & Agrawal, 1995) and polynomial mutation operator (Deb & Goyal, 1996) are used. These two operators are extended for bounded variables (Deb, 2000), thus, are adopted to deal with the box constraint of the form features. The SBX and polynomial mutation operators are calculated based on the polynomial probability distribution. An extra parameter called distribution index (DI) needs to be determined. Here, both DI values for the two operators are set to 1. Their practical usage is quite straightforward by simply assigning the crossover and mutation probability, which are taken as 0.9 and 0.1 respectively. When a pre-defined number of generations (say 50) is reached, the product form searching is terminated.

5. Results and discussions

5.1. Predictive performance of the SVR models

The optimal parameters obtained from 5FCV were used to construct the prediction models of AR for three adjective pairs including traditional-modern, heavy-handy, and rational-emotional. The optimized parameter set \((C, \varepsilon, \sigma^2)\) for three adjective pairs were \((2,7.63E−06,1.41)\), \((0.5,3.13E−02,1.41)\), and \((1.31E+05,3.13E−02,362.03)\), respectively. Fig. 5 shows the predictive performance of the three SVR models. It can be observed that the predictive adjective scores (drawn in red dash line) fit well to the original scores (drawn in blue solid line) of the 69 mobile phone samples. The RMSE of the three training model were 0.046, 0.092, and 0.056. The correlation coefficients between the original scores and the predictive scores were also calculated as 0.99, 0.94, and 0.97. The prediction models of AR for these three adjective pairs all have great performance. Note that the prediction model for rational-emotional performed slightly worse than the other two models. According to the author’s observation, the feeling of rational-emotional is often closely related to the color and texture information of the product samples. Since the information was ignored in the SD experiment, it might be the reason for the degradation of the predictive performance.
5.2. Comparison of single and multiple affective response optimizations

In order to demonstrate the differences between SOO and MOO optimization, a simple problem (Problem 1) with two affective dimensions (traditional-modern and heavy-handly) to be optimized is first considered. This optimization problem aims to find out the most traditional and handy product alternatives. Although the subjects can evaluate the product samples with a score ranged from -1 to +1 (see Sect. 4.2), the averaged adjective scores in the training data fed to the SVR model typically distributed in a smaller interval (see Fig. 5). Therefore, in this study, the target values will be automatically assigned as the largest (in absolute value) obtained from the SD experiment, instead using the extreme value of -1 or +1. For SAR optimization, product form design is searched to minimize the weighted absolute error of the two affective dimensions between the target value and the predictive value using traditional GA. The weight value of each affective dimension was assigned as 0.5. Similar problem formulation can be found in the studies of Hsiao & Tsai (2005) and Tsai & Chou (2007). In their studies, the target value and the weight value for each affective dimension can be assigned by the designers. In this study, the designers can only determine to maximize or minimize the designate affective dimensions. For MAR optimization, product form searching is conducted using NSGA-II as described in Sect. 4.4.

Fig. 6 illustrates the SOO using traditional GA for Problem 1. The process converges very quickly within five generations. The weighted absolute error of the two adjectives is 0.092 in the fourth generation and improves very slightly in the following generations. For optimizing product form design to maximize or minimize designate affective dimensions, the designers may be interested in finding one single best solution. For this purpose, the SOO using traditional GA for product form searching is applicable. However, ARs toward product samples are typically complex and conflicting with each other. The optimized product alternative for one affective dimension may fail to be the best one for another dimension. The characteristic of the Pareto set in the final generation for Problem 1 obtained from the MOO is shown in Fig. 7. By interpreting the results of the MOO, the trade-offs between the affective dimensions can be investigated. The adjective pair “traditional-modern” is denoted as affective dimension #1 while affective dimension #2 heavy-handly. As shown in Fig. 7, the best solution for affective dimension #1 was (-0.173, 0), which means the target value of dimension #1 was -0.173, and the target value of dimension #2 was 0.
Similarly, the best solution for affective dimension #2 was (0, 0.203), which induces large absolute error for dimension #1. For minimizing the error of both dimensions at the same time, the solution was (-0.103, 0.099). In order to examine the convergence of NSGA-II, the uniformity and spread of solutions along the Pareto front can be used to identify whether one approximation set is better than another based on certain set preference relations. Instead of using an eye estimate, the mean and the standard deviation of the crowding distance can be used, which was suggested by Kasat & Gupta (2003). Fig. 8 shows the mean and standard deviation of the crowding distance for the Pareto set (population size = 200). The optimization process converges after about 35 generations.

5.3. Applicability of the proposed method

The applicability of the proposed HKES based on MARs for product form design was demonstrated using Problem 2 with three affective dimensions, including traditional-modern (dimension #1), heavy-handy (dimension #2), and rational-emotional (dimension #3), to be optimized. The objective of Problem 2 is to find out the most traditional, handy, and rational product alternatives. The MOO process using NSGA-II for Problem 2 was shown in Fig. 9. The setting of NSGA-II follows the description in Sect. 4.4 with the population size 200 and the generation number 50. According to the optimization process, the mean (Fig. 9[a]) and standard deviation (Fig. 9[b]) of the crowding distance for the Pareto solutions decrease very rapidly in the first 10 generations and converge surely to the minimum within 50 generations.

The Pareto set in the final generation for Problem 2 is shown in Fig. 10. Each product form design alternative can be drawn in a three-dimensional space which composed of the three affective dimensions. It is cumbersome to interpret the results merely by an eye investigation. Therefore, these design alternatives were further analyzed by separating them into groups. Many clustering methods such as k-means clustering, self-organizing maps and fuzzy c-means clustering can be used for this purpose. In this study, k-means clustering as a simple and popular method was adopted. The effects of using different number of clusters from 2 to 7 were examined.
The result for clustering into four groups is shown in Fig. 10. The centroids of four clusters are marked by a red cross (denoted as Cluster 1-4) and the alternatives of each cluster are colored in green, blue, yellow and purple, respectively. It was observed from Cluster 1 that large absolute values of affective dimensions #1 and #3 were accompanied by smaller absolute values of affective dimension #2. However, a large absolute value in affective dimension #2 can substantially reduce the absolute values of the other two dimensions (see Cluster 4). A compromise can be made by yielding medium absolute value in all the three affective dimensions (see Cluster 2). Representative design alternatives can also be selected from these clusters in the Pareto set according to the trade-offs between the affective dimensions.

6. Conclusions

As a kind of consumer-oriented technology, KES is very useful for modeling subjective human perceptions and analyzing product form features systematically. This study proposes HKES based on MARs using SVR and MOGA for product form design. In BKES for modeling consumers’ AR, the SVR model for each affective dimension was trained using the form features of product samples and the AR evaluation data gathered from the questionnaires. In FKES for generating design alternatives, the MOGA-based searching is capable to produce Pareto-optimal front solutions which satisfied with the input MARs specified by a product designer. In the case study of mobile phone design evaluated with three adjective pairs, including traditional-modern, heavy-handly, and rational-emotional, the predictive performance of the SVR models for each affective dimension is very satisfactory. When it comes to search optimal product form design, the analysis provided from NSGA-II allows the designers to investigate the trade-offs between the three affective dimensions, instead of obtaining one single optimal solution from traditional GA. In the future, consistent efforts will be made to apply the proposed HKES to a wide variety of product design.

References


Fig. 1. A typical scheme of the HKES for SAR.
Fig. 2. The proposed HKES for MARs.
Fig. 3. An interface of questionnaire for adjective evaluation.
Fig. 4. Training scheme of the SVR model.
**Fig. 5.** Predictive performance of SVR model for (a) traditional-modern, (b) heavy-handy, and (c) rational-emotional.
Fig. 6. SOO process using traditional GA of for Problem 1.
Fig. 7. Pareto set description in the final generation for Problem 1.
Fig. 8. (a) Mean and (b) standard deviation of the crowding distance for the Pareto solutions during the MOO process (Problem 1).
Fig. 9. (a) Mean and (b) standard deviation of the crowding distance for the Pareto solutions during the MOO process (Problem 2).
Fig. 10. Pareto set description in the final generation with respect to (a) dimension #3 — dimension #2 and (b) dimension #1 — dimension #2 for Problem 2; Red crosses denote the centroid of each cluster.
Table 1. Complete list of form features of mobile phone design.

<table>
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<tr>
<th>Form features</th>
<th>Type</th>
<th>Attributes</th>
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<tr>
<td>Length ((x_1))</td>
<td>Continuous</td>
<td>None</td>
</tr>
<tr>
<td>Width ((x_2))</td>
<td>Continuous</td>
<td>None</td>
</tr>
<tr>
<td>Thickness ((x_3))</td>
<td>Continuous</td>
<td>None</td>
</tr>
<tr>
<td>Volume ((x_4))</td>
<td>Continuous</td>
<td>None</td>
</tr>
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<td>Type ((x_5))</td>
<td>Discrete</td>
<td>Block body ((x_{5-1}))</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Flip body ((x_{5-2}))</td>
</tr>
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<td></td>
<td></td>
<td>Slide body ((x_{5-3}))</td>
</tr>
<tr>
<td>Type ((x_6))</td>
<td>Discrete</td>
<td>Full-separated ((x_{6-1}))</td>
</tr>
<tr>
<td></td>
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<td>Partial-separated ((x_{6-2}))</td>
</tr>
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<td></td>
<td></td>
<td>Regular-separated ((x_{6-3}))</td>
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<td>Style ((x_7))</td>
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<td>Round ((x_{7-1}))</td>
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<td>Number button ((x_9))</td>
<td>Discrete</td>
<td>Square ((x_{9-1}))</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Vertical ((x_{9-2}))</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Horizontal ((x_{9-3}))</td>
</tr>
<tr>
<td>Panel</td>
<td>Detail treatment ($x_{10}$)</td>
<td>Discrete</td>
</tr>
<tr>
<td>-------</td>
<td>---------------------------</td>
<td>----------</td>
</tr>
<tr>
<td></td>
<td>Position ($x_{11}$)</td>
<td>Discrete</td>
</tr>
<tr>
<td></td>
<td>Shape ($x_{12}$)</td>
<td>Discrete</td>
</tr>
</tbody>
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