A Consensus Prediction Model of Affective Responses in Kansei Engineering System

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Abstract

In the product design field, modeling consumers’ affective responses for product form design is very helpful for developing successful products. However, despite a vast amount of literatures available on the subject, the heterogeneous nature of consumer preference patterns is often neglected thus the resulting prediction model is of less value for the real-world application. In the present paper, a Kansei engineering method is proposed to construct the unified consensus prediction model for consumer’s affective responses based on the concepts of consumer segmentation and information fusion. First, a fuzzy c-means (FCM) clustering is applied to separate the consumers with heterogeneous preference patterns into homogenous groups. In every consumer group, the relative importance of each consumer and the interaction between pairs of consumers can be determined according to the results of the FCM clustering. Secondly, a state-of-the-art machine learning approach known as “support vector regression (SVR)” is used to construct the individual prediction model for each consumer. These individual models have out-performing predictive ability of the affective responses for each consumer due to the good generalization performance of the SVR algorithm. Finally, a fuzzy integral aggregation operator, namely the 2-additive Choquet integral, is used to combine the SVR models and also taking into account the relative importance and interaction of consumers in the consumer group. By using the proposed framework, consumers’ affective responses toward product form design can be predicted precisely by individual prediction model and the target consumer groups can be clustered meaningfully by visualized way. Furthermore, consumers’ affective responses of the target consumer groups could be gathered more rationally.

Keywords: Affective Response, Product Form Design, Kansei Engineering, Fuzzy C-Means Clustering, Support Vector Regression, 2-Additive Choquet Integral.

1. Introduction

In today’s highly competitive market, the benefits provided by products must meet the consumer’s needs to ensure the success of enterprises. The degree of consumer’s affective responses, as a critical criterion to measure if a product meets the needs of a consumer, is very important for choosing attractive product design to consumers. Aim at capturing consumer’s preference and relate it into the products, the problem of modeling affective responses can be found in many disciplines. For example, consumer preferences related to product attributes have been studied intensively in the field of consumer research. In food industry, the research of hedonics emphasizes to analyze the characteristics of food, such as outward appearance and the chemometrics data, and examines their effects on the consumer’s feelings [1]. The study of emotional responses in product design explores how to design products triggering ‘happiness’ in consumer’s mind and find out which product attributes help in communication of positive emotions [2]. In landscape design, client can describe the garden by adjective words then see the view of the proposed design through a three-dimensional virtual reality system [3]. The purpose of these researches is trying to connect consumer’s affective responses to the target products regardless that they are described with different domain-specific product attributes.

Product differentiation as a marketing strategy assumes that providing diversity or variations of products according to consumer’s demand is helpful to obtain a horizontal share of a broad market [4]. However, for mature products which have similar functionality and specification, such as consumer electronics, it is difficult to design a product effectively and make it fit the consumer’s need well.
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 systematic product design studies have been carried out to get a better insight into consumers’ subjective responses. Kansei engineering originated from Japan [5] is the most notable research which has the basic assumption that there exists a cause-and-effect relationship between consumers’ affective responses and product form features. The prediction model can be constructed by consumer’s evaluation data gathered from questionnaire investigation and the form features of the evaluated product samples. Using the prediction model, the relationship between affective responses and product form design can be analyzed and especially designed product form for specific target consumer groups can be produced more objectively and efficiently.

In the literatures of Kansei engineering, it hasn’t been pointed out explicitly that the complexity for modeling affective responses is mainly due to its multiple-consumer versus multiple-product nature. The construction of the prediction model is often involved with large amounts of consumers with heterogeneous needs and a wide variety of products. Two different schemes including single-consumer/multiple-product and multiple-consumer/single-product can be identified to clarify this modeling problem. On the one hand, the single-consumer/multiple-product scheme can be regarded as a kind of personal preference profiles concerning with various product alternatives. Similar ideas can be found in the research of online recommendation system or e-commerce applications. Instead of providing personal recommendation for individual customer only, unified suggestion for certain target group of consumer, called collaborative recommendation, is often of greater interest [6]. However, the potential to combine individual single-consumer/multiple-product models into one unified suggestion model is seldom to be mentioned in the product design field.

On the other hand, the multiple-consumer/single-product scheme, which is frequently used in Kansei engineering research, deals with the consumer’s data by averaging individual consumer evaluation data for the same product. The problem of data averaging of consumer evaluation data is that using the averaged data can only capture the most manifest trends in consumer satisfaction patterns [7]. Since the consumer affective responses are usually heterogeneous in nature, averaged consumer data may fail to represent any individual opinion [8]. Another strategy to handle the consumer data called “mean centering”, in which the variance for individual consumer is taken into consideration, suffers the same shortcoming [9].

In the authors’ previous studies [10-12], state-of-the-art machine learning approaches were used to relate consumers’ affective responses and a product’s form features. More sophisticated expert systems, such as the classification-based Kansei engineering system [13] and the hybrid Kansei engineering system [14], can also be constructed to facilitate product design.

This study proposed a Kansei engineering method to construct the consumer affective response model of product form design based on the concepts borrowed from consumer segmentation and information fusion. In the proposed method, a fuzzy c-means (FCM) clustering is applied to separate the consumers with heterogeneous opinions into homogenous groups of consumers with similar preferences. The preference data of consumers evaluating on the representative product samples is used as segmentation variable. In every homogenous cluster, the relative importance of each consumer can be determined by the membership grades while the interaction between pairs of consumers determined by their distance in a multidimensional scaling space. The product form features used as input data and the adjective evaluation scores gathered from questionnaire as output values are used to construct the prediction model of affective responses for each consumer by using support vector regression (SVR). In order to deriving a unified consensus model for each homogenous group and combine the prediction model of each consumer in the group, a fuzzy integral method, namely the 2-additive Choquet integral, is used to aggregate the output value of individual consumer prediction model considering the importance and interaction of consumers within the group.

The reminder of the paper is organized as follows. Section 2 to 4 review the background of affective response modeling, consumer segmentation, and information fusion. Section 5 presents the proposed consensus prediction model of affective responses in Kansei Engineering System. Finally, the conclusions are given in Section 6.
2. Prediction model of affective responses

One of the frequently encountered problems for modeling affective responses is how to deal with the nonlinear relationship between the product form features and the affective responses of consumer [15-17]. There exist various methods which can be used to construct the prediction model regarding it as a regression/function estimation problem. The mostly adopted techniques in the product design field such as multivariate analysis [18], multiple linear regression [19] and partial least squares regression [1] 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.

In order to deal with the nonlinearity causes by the large amounts of consumers and product samples, a variety of nonlinear modeling techniques are available as an alternative to model the nonlinearity, however, they have some shortages. The quality attributes are classified into five categories (i.e., performance, excitement, indifference, and reverse) before building the Kano’s model. The main controversy of Kano’s model is the classification methodology so that various researchers propose different way for classification [20-22]. The famous “black-box” methods including neural networks (NN) [23, 24] and SVR [10, 25] are good candidates for building the prediction model. Also, endowed with numerous highly-evolving techniques developed in machine learning, NN and SVR have great potential to construct real-world applications instead of in-lab research. For example, equipped with reliable techniques for model/parameter selection, such as cross-validation, ensemble learning [26], and Bayesian inference [27], one can obtain best generalization performance and reduce the overfitting problem. Unfortunately, the learned resulting model and the parameters are difficult to interpret for NN. This difficulty is caused by the nature of the NN algorithm to revise connections which are not used currently.

Beside the linear/nonlinear issue, it is a common situation for modeling affective response model to involve with large amounts of consumers and product samples. [28] used clustering technique for reducing the dimension of data for fuzzy rule-base prediction model. The capability to integrate with fuzzy set and rough set [29] is beneficial for processing the analytical data in the format of imprecise and vague information in product design but suffer from the same shortcoming. Therefore, the technique of “mixture of expert” [30], which is often used as a divide-and-conquer scheme for large dataset [31] such as pattern recognition, is also very suitable to reduce the complexity of the prediction model with large amount data of consumers and problems. The concept is dividing the problem into simpler sub-problems, conquering the sub-problems with sub-models and combining the sub-models to be the final solution. These ideas are yet be explored widely in the product design field.

3. Consumer segmentation

Since [4] presented the concept of consumer segmentation, it has become an important marketing strategy. It is known that the need of consumer is often diverse and heterogeneous. By distinguishing different homogeneous groups, more precise adjustment of product alternatives to these consumer groups can be made. In order to recognize the consumer heterogeneity effectively, the choice of relevant segmentation variables and the methods used to construct segments are two critical factors. Different consumer characteristics such as demographics, lifestyle, socio-economic factors, purchase behavior, attitudes/preference toward product alternatives etc., can be used as segmentation variables to construct segments. For example, [32] had identified five distinct types of consumer segmentation according these segmentation variables. In this study, the affective response is regarded as a kind of consumers’ needs. Thus, the segmentation variables should be capable to reflect consumers’ preferences toward product design. The variables such as demographics, lifestyle and other factors which are frequently used in marketing research do not directly connected to the product itself thus were not suitable for consumer segmentation in product design. On the contrary, the preference data of consumers evaluated on the representative product samples is more suitable to be used as segmentation variable for affective response research in product design [33].

The construction of consumer segmentation had commonly applied cluster analysis. The purpose of cluster analysis is to construct homogenous groups with respect to the segmentation variables. Various methods including K-means clustering [34], self-organizing maps [35], FCM clustering [9], and
support vector clustering [36] had been used for consumer segmentation. Among these methods, FCM clustering is the most robust method compared to other non-fuzzy clustering for consumer segmentation [37]. FCM clustering is known as being capable to deal with the overlapping clusters and is stable even in the presence of outliers [38]. The main reason of its superiority is due to the production of the fuzzy partition in which each data point is associated with a set of membership grades indicating the degrees of the point belonging to the different clusters. The distances between data points in the clustering results also provide useful information to understand their mutual relation. For visualizing the projection of high dimensional dataset onto low dimensional graphical, principal component analysis and Sammon mapping are the two frequently used techniques for visualization of the clustering results. FUZZSAMM algorithm [39], which is a modified version of Sammon mapping, is more suitable for human inspection compared to other visualization techniques [39]. Therefore, FCM clustering with FUZZSAMM algorithm is very suitable for the application of consumer segmentation.

4. Information fusion

Information fusion has drawn considerable interests in the field of multicriteria decision making and pattern recognition in recent years [40]. It involves with merging different information sources to obtain the consensual opinion. Hence, it is very suitable to combine preference information consists of subjective description of a group of people. The simplest way to perform information fusion is via the use of aggregation operator. A complete review of the existing aggregation operators can be found in the paper of [41]. The crux of information fusion problem is to choose a suitable aggregation operator and then different pieces of information can be combined to obtain a unified consensus. However, due to the inherent interaction among diverse information sources, classical operators such as average, minimum, maximum even for more generalization in the additive form do not work well in the real world problems [42]. Moreover, it has been mentioned in [40] that, although averaging operators are natural candidates for merging preference data, they are not suitable for data expressed in bipolar scales which were appeared frequently in the study of consumer preferences.

Another crucial issue of information fusion is to determine the relative importance of different information sources, or more generally, to express the inherent interaction among various information sources. For resolving the interaction between information sources, the fuzzy integral is superior to other classical aggregation operators by providing a more intuitive and effect manner with the aid of nonadditive set function on the power set of all information sources [43]. The Choquet integral can be regarded as the generalized weighted mean operator and the Sugeno integral as the generalized weighted maximum and weighted minimum operators [44]. These two variants of the fuzzy integral have also been proven to be valuable tools to deal with the information fusion problem [45, 46]. It is also possible to integrate domain knowledge for determining the importance and interaction of information sources automatically. For example, to obtain membership grade of image pixel from the grey-level property [47], incorporate with spatial information into the decision making problem [48], or generate the weight distributions of aggregation operators based on probability density functions [49] etc. Inspired by these ideas, the density and the distribution of the information sources obtained from the results of consumer segmentation based on fuzzy clustering can be used to aggregate the affective responses of consumers.

5. A consensus prediction model of affective responses

A typical prediction model of consumer’s affective responses in Kansei engineering is shown in Figure 1. This kind of model does not take into account the diversity and heterogeneity of consumer responses. More specifically, the prediction model only captures the most manifest trends by aggregating the affective response data $y_1, ..., y_n$ of $n$ consumers using the certain aggregation operator $A_{Ag}$, such as the arithmetic average operator or the mean centering technique. In fact, even the effects of different aggregator operators have not been studied extensively in the field of Kansei engineering. Moreover, considering the performance of the methods used to construct the model, e.g. multiple linear regression and partial least squares regression, can only deal with the linear relationship between the product form features $x_1, ..., x_n$ and the aggregated consumer response $y_{A_{Ag}}$ of all
consumers. The resulting prediction model is of less value to construct the real-world applications.

This study proposes to overcome the shortcomings of the typical prediction model based on the concepts of consumer segmentation and information fusion. The proposed model is consists of three parts including construction of consumer groups, construction of affective response model for individual consumer and construction of the unified consensus prediction model.

An overview of the proposed model is shown in Figure 2. First, with the aid of FCM clustering using the consumer’s preference data evaluated on the representative product samples, all consumers are grouped into different clusters. Consumers $S_1, ..., S_n$ within each consumer group are regarded as information sources with similar preferences. Two characteristics of information sources including the relative importance $w_i$ of the consumers and the interaction $I_{ij}$ between pairs of consumers are considered. The importance $w_i, ..., w_n$ of consumers $S_1, ..., S_n$ are calculated according to their membership grade $\mu_1, ..., \mu_n$ belongs to the consumer group. The interaction $I_{ij}$ between all pairs of consumer $S_i$ and $S_j$ are calculated according to the distance $d_{ij}$ in a multidimensional scaling space.

Secondly, a series of SVR prediction models $SVR_1, ..., SVR_n$ are then constructed for consumers $S_1, ..., S_n$ in the consumer group. The product samples are decomposed into form features $x_1, ..., x_m$ using morphological analysis. Training of these prediction models can be done by taking $x_1, ..., x_m$ as input data while the individual response $y_1, ..., y_n$ toward every product samples as output values. By choosing suitable parameters of the training model, these individual models will have out-performing predictive ability of the responses for each consumer due to the good generalization performance of the SVR algorithm.

Finally, the 2-additive Choquet integral aggregation operator is used to combine the consumer’s individual response $y_1, ..., y_n$ of the SVR models $SVR_1, ..., SVR_n$ and obtains an aggregated response $y_{Ag}$ for each consumer group. The aggregation operator not only integrates the individual response $y_1, ..., y_n$ but is also capable to handle the relative importance $w$ of each consumer and the interaction $I$ between pairs of consumers. In a consequence, a unified consensus prediction model for each consumer group can be derived. Consequently, the proposed method is very suitable for modeling the affective responses of consumers which exhibit with heterogeneous preference patterns while maintain high predictive performance for product samples with unknown affective responses.

![Figure 1. A typical prediction model in Kansei engineering.](image)

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6. Conclusions

The consensus prediction model of affective responses is an important issue in the Kansei engineering system. Without using the classical operators such as average, minimum and maximum, the consumer’s affective prediction model is constructed by using SVR technique for each consumer. This is the concept of dividing the problem into sub-problems. In order to emphasize the difference of consumers, FCM clustering with the fuzzy membership grades is used for calculating the importance of each consumer, and the interactions between consumers. Finally, these sources, including the individual consumer’s affective prediction model and the parameters getting from FCM clustering, are dealt with the 2-additive Choquet integral aggregation operator for the final consensus prediction model. The consensus prediction model is one part of the main research being taken by the laboratory under the guidance of Meng-Dar Shieh. Nerveless, more case studies using different kinds of products, such as consumer electronics, furniture, automobiles, etc., are still needed to verify the effectiveness of the Kansei engineering system framework.

References

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