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A hybrid Kansei engineering design expert system based on grey system theory and support vector regression

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ABSTRACT

Nowadays customers choose products strictly in terms of their specific demands. How to quickly and accurately catch customers' feelings and transform them into design elements and vice versa becomes an important issue. This study explores the bi-directional relationship between customers' demands or needs and product forms by using a novel integral approach. High-price machine tools are used as our demonstration target. This integral approach adopts the "grey system theory (GST)", and the state-of-the-art machine learning based modeling formalism "support vector regression (SVR)" in the "Kansei engineering (KE)" process. The GST is used to effectively determine the influence weighting of form parameters on product images and the SVR is used to precisely establish the mapping relationship between product form elements and product images. Furthermore, for practical concerns, a user-friendly design hybrid design expert system was developed based on the proposed novel integral schemes.

1. Introduction

Consumers are now strict in choosing products in terms of their demands. The key factor that influences the success of a new product is capturing the "voice of the customer." Satisfying customers' requirements is not only a "need" but also a "must" for every company.

While there are various customers' needs, the functional and affective needs have been recognized to be of primary importance for customer satisfaction (Khalid, 2001). For functional needs, design for performance (e.g. functional design) and design for usability (e.g. ergonomic design) now rarely empower a competitive edge because product technologies mature, or competitors can quickly catch up (Khalid, 2004). Thus it is imperative to design products by engaging customers' emotions or affects.

Affect is said to be a customer's psychological response to the perceptual design details (e.g. styling) of the product (Demirbilek & Sener, 2003). Affect is a basis for the formation of human values and human judgment. For this reason it might be argued that models of product design that do not consider affect are essentially weakened (Helander & Tham, 2003). For example, despite the basic needs of function and usability for a product, some high-price merchandise such as cars or CNC (computer-numerical-control) machine tools, the factor of affective appearance has deterministic influence on customers in deciding whether to purchase or not.

The main challenge for affective design is to grasp the customers' affective needs accurately and subsequently to design products that match these needs. In particular, Kansei engineering (Nagamachi, 1996) has been developed as a comprehensive consumer-oriented technology for new product development.

Kansei is a Japanese word which means a consumer's psychological feeling and image regarding a new product. By Kansei words, the customers are guided to express their affective needs, their feelings, and their emotional states. These emotional and sensory wants are then translated into perceptual design elements of the product. Kansei engineering (KE) is defined as "the translating technology of a consumer's feeling and image for a product into design elements." It has been successfully applied in the field of product design (Guan & Lin, 2001; Ishihara, Ishihara, & Nagamachi, 1995) to explore the relationship between the feelings of the consumers and the design elements of products.

As such, this study aims to present a novel effective approach based on the KE scheme to establish the perception of the image of a CNC machine tool against its form elements. Meanwhile, to facilitate the usability of our proposed mapping model, a design expert system is developed. Through the help of this expert system, designers can easily capture customers' needs, and develop new product appearances based on the obtained information.

The structure of this study is as follows. Section 2 describes the background review. Section 3 illustrates the methodology. Section 4 explains the implementation details of KE. Section 5 presents the

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proposed mapping relationship regarding the customization for CNC machine tools. Section 6 presents the performance evaluation of our proposed model. Section 7 discusses the development of a design expert system. Finally, the conclusion is drawn in Section 8.

2. Background review

Approaches to capture, analyze, understand and project customers' needs have received a significant amount of interest (McKay, de Pennington, & Baxter, 2001). And, there were two approaches so far found in past researches related to how to grasp customers' needs: the qualitative and the quantitative approaches.

For the qualitative approach, some published methods (Griffin & Hauser, 1992; LaChance-Porter, 1993) are helpful for discovering the customers' needs, but it is still difficult to obtain design requirement information because customers and marketing people do not necessarily understand what design engineers need to know.

On the other hand, for the quantitative approach, Shoji, Graham, and Walden (1993) used semantics methods, such as the Kawakita Jiro (KJ) method and multi-pickup method (MPM) to discover underlying facts from affective language. Jenkins (1995) used linear regression analysis and Louviere, Anderson, White, and Eagle (1990) used the conjoint method to measure preferences for different product profiles. Turksen and Willson (1992) employed fuzzy systems to interpret the linguistic meaning regarding customers' preferences as an alternative to conjoint analysis. Hauge and Stauffer (1993) developed taxonomy of product requirements to assist in traditional qualitative market research. As for how to translate customers' needs into products' form elements, some studies presented the method of quality function deployment (Clausing, 1994; Fung & Popplewell, 1995; Fung, Tang, Tu, & Wang, 2002) to aid the designer's view in defining product specifications. Furthermore, McAdams, Stone, and Wood (1999) proposed a matrix approach to the identification of relationships between customers' needs and product functions.

Apart from the aforementioned techniques, a popular methodology to translate consumers' psychological feelings about a product into perceptual design elements is "Kansei engineering." Nagamachi (1996) proposed six technical styles of KE methods with applications to the automobile industry, cosmetics, house design, and sketch diagnosis. Nadia (2001) adopted Kansei modeling to reduce the uncertainty and complexity involved in the mapping between visual expressions and impressive words used to convey them. Hajime (2002) explored a unique field of food KE. Ishihara et al. (1995) applied neural network techniques to enhance the inference between Kansei words and design elements in Kansei design systems. Matsubara and Nagamachi (1997) developed hybrid expert systems for Kansei design support. Helander and Tay (2003) investigated if the same Kansei words could be used to describe four different types of kitchen appliances.

Although the KE is superior for mapping the customers' Kansei into design elements and vice versa, the requirement for seeking more accurate mapping relationships never stops. In the past, some mapping schemes were proposed, such as grey theory, neural network, fuzzy logic, linear regression, and so on (Hsiao & Liu, 2004; Hsiao & Tsai, 2005; Jiao, Zhang, & Helander, 2006; Kinoshita, Ichinohe, Sakakura, Cooper, & Kamei, 2007; Lai, Lin, & Yeh, 2005; Tsai & Hsiao, 2004). However, these models have their own deficits and limitations and are not accurate enough. Among the proposed models, the artificial neural network (ANN) was popular in building relationships between customers' intension and products' form elements. However, the ANNs are considered to be "black-box" models since their performances depend merely on the size and quality of the data, and the structure of the model. A drawback of ANNs, which is shared by all types of black-box models, is that the resultant model and its parameters are difficult to interpret from the viewpoint of gaining insight into the data used in the model building exercise. In other words, although some ANN models performed well in predicting conditions similar to those encountered during training, they were unable to arrive at accurate predictions under conditions drastically different from the training conditions. Another prime difficulty observed in using ANN models was that they can deal only with certain types of conditions and needed human intervention in selecting the useful data set and parameters that could be used to train the model most effectively. Additionally, most of the proposed models lack of effective data processing scheme, thus the modeling work is time consuming and its result is doubtful. It is therefore strongly needed to handle raw data which are inadequate, vague, or reluctant in essence, so as to reduce the modeling load, and make the modeling work more efficient and accurate.

To solve the aforementioned problems, this study integrates grey system theory (GST), support vector regression (SVR) in conjunction with KE, to effectively and accurately establish the bi-directional mapping relationship between product images and products' form elements. The GST is adopted due to its superiority in handling those vague, fuzzy, or grey data. The SVR is used because of its good ability in solving nonlinear mapping problems.

3. Methodology

The GST (Deng, 1989) has been developed to check the relationship among factors in an observable system where the information available is uncertain and incomplete. It has been successfully used in a wide range of fields to handling of incomplete known information for exploring unknown information. In this study, we adopt the GM(1,N) model of GST to solve the relative influence weighting of product's form elements on products' images where the collected data are grey in essence.

More recently, a machine learning theory based formalism known as SVR (Vapkin, Golowich, & Smola, 1997) that shares many of its features with the ANN, but possesses some additional desirable characteristics, is gaining widespread acceptance in data-driven nonlinear modeling applications. Specifically, the SVR scheme has the following advantages: (1) good generalization ability of the regression function, (2) robustness of the solution, (3) sparseness of the regression and an automatic control of the solution complexity, (4) providing an explicit knowledge of the data points, which are important in defining the regression function. This SVR feature allows an interpretation of the SVR-approximated model in terms of the training data. In this study, the SVR is used to map the product image against product form elements and vice versa, in which the mapping relationship is highly non-linear in essence.

Following are the details of three aforementioned schemes used in this study.

3.1. Grey system theory

The GST is based on the assumption that a system is uncertain, and that the information regarding the system is insufficient to build a relational analysis or to construct a model to characterize the system (Deng, 1989). The grey system puts each stochastic variable as a grey quantity that changes within a given range. It does not rely on statistical method to deal with the grey quantity. It deals directly with the original data, and searches the intrinsic regularity of data (Tseng, Tzeng, & Yuan, 1997). The GST includes the following fields: (a) grey generating, (b) grey relational analysis, (c) grey forecasting, (d) grey decision making, and (e) grey control.