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Comparison of multi-objective evolutionary algorithms in hybrid Kansei engineering system for product form design

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ABSTRACT

Understanding the affective needs of customers is crucial to the success of product design. Hybrid Kansei engineering system (HKES) is an expert system capable of generating products in accordance with the affective responses. HKES consists of two subsystems: forward Kansei engineering system (FKES) and backward Kansei engineering system (BKES). In previous studies, HKES was based primarily on single-objective optimization, such that only one optimal design was obtained in a given simulation run. The use of multi-objective evolutionary algorithm (MOEA) in HKES was only attempted using the non-dominated sorting genetic algorithm-II (NSGA-II), such that very little work has been conducted to compare different MOEAs. In this paper, we propose an approach to HKES combining the methodologies of support vector regression (SVR) and MOEAs. In BKES, we constructed predictive models using SVR. In FKES, optimal design alternatives were generated using MOEAs. Representative designs were obtained using fuzzy c-means algorithm for clustering the Pareto front into groups. To enable comparison, we employed three typical MOEAs: NSGA-II, the Pareto envelope-based selection algorithm-II (PESA-II), and the strength Pareto evolutionary algorithm-2 (SPEA2). A case study of vase form design was provided to demonstrate the proposed approach. Our results suggest that NSGA-II has good convergence performance and hybrid performance; in contrast, SPEA2 provides the strong diversity required by designers. The proposed HKES is applicable to a wide variety of product design problems, while providing creative design ideas through the exploration of numerous Pareto optimal solutions.

1. Introduction

In today's highly competitive market, the trend in product design is moving toward a consumer-centered approach. Determining the means to satisfy the needs of customers is a crucial issue in every company. Affective responses, which are a reflection of consumers' affective needs, are also attracting increased attention. Kansei engineering is a method used for the translation of affective responses to products into design elements, and has been applied with considerable success in the field of product design [1].

The hybrid Kansei engineering system (HKES) was first proposed by Matsubara and Nagamachi [2] for the automatic generation of products capable of meeting the affective needs of customers. Several studies have been conducted on the applicability of HKES. Hsiao and Tsai [3] proposed a hybrid method for product form design with which to obtain the affective responses of various product forms using a parametric approach. They identified four kinds of affective responses and built predictive models using neural network. On the basis of the trained networks, the values of the four kinds of affective responses are integrated into a single number using a linear weighted sum method, whereupon the optimal product form is obtained using a genetic algorithm. Hong et al. [4] adopted multiple linear regression for the establishment of a model for the prediction of affective responses. In the process of optimization, they employed goal programming to find the optimal design wherein the mean response was close to the target value, while the standard deviation response was kept as small as possible. Guo et al. [5] presented a systematic method for affective design integrating a back propagation neural network (BPNN) and genetic algorithm to obtain near-optimal design. BPNN was used to construct the nonlinear relationship between design variables and affective responses and to serve as the fitness function in a genetic algorithm. These studies all dealt with multiple affective responses; however, in the process of optimization, they all transformed the multi-objective optimization problem into a single-objective optimization problem through the use of classical methods such as linear weighted sum or goal programming. As a result, none of these methods are able to

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provide more than one solution in any simulation run. This approach provides simplicity, and ease of implementation; however, it tends to limit the search space, which prevents consideration of all possible solutions.

From the perspective of multi-objective decision making (MODM), three approaches can be adopted in accordance with the timing of the decision maker (DM) with regard to the articulation of preferences: prior, progressive, and posterior preference articulation approaches [6]. The transformation of a problem from one with multiple objectives to a single objective belongs to the prior preference articulation approach. Progressive preference articulation requires that preference information be incorporated within the problem during the problem-solving process. The interactive genetic algorithm (IGA), which is widely used in product design [7], falls into this category. IGA is similar to HKES in seeking to construct a relationship between the variables in product design and affective responses. It employs a fitness function based on user evaluations for the generation of optimal designs in accordance with user preferences [8]. Nevertheless, IGA requires that users engage in a large number of tiresome evaluations. Moreover, individual preferences are constantly being adjusted even during the process of evaluation, resulting in noise associated with the fitness values.

The multi-objective evolutionary algorithm (MOEA) adheres to the posterior preference articulation approach, which does not require advance information with regard to the preferences of the DM and provides numerous Pareto optimal solutions in a single run. In recent years, the application of MOEA has become a new topic in Kansei engineering. Yang [9] proposed the application of MOEA in product affective design, and successfully constructed HKES which used support vector regression (SVR) to predict affective response, and non-dominated sorting genetic algorithm-II (NSGA-II) to search for optimal design. In this way, Pareto front, which has many optimal form designs, was obtained. Similarly, Su et al. [10] used the neural network to build a predictive model, and the NSGA-II to optimize. In addition, Jiang et al. [11] combined two affective targets with two customer satisfaction targets in their study. Particle swarm optimization (PSO)-based adaptive neural fuzzy inference system (ANFIS) and chaos-based fuzzy regression were employed to build predictive models, and chaos-based NSGA-II is used to search for the optimal design. Many previous studies have used NSGA-II to investigate multiple affective responses; however, there have been few attempts to use the Pareto envelope-based selection algorithm-II (PESA-II) or strength Pareto evolutionary algorithm-2 (SPEA2). NSGA-II, PESA-II, and SPEA2 are representative MOEAs of the second-generation algorithms characterized by an emphasis on efficiency and the use of elitism. The performance of MOEAs commonly differs according to the problem at hand; therefore, it is worthwhile considering which method is best suited for application in Kansei engineering. To the best of our knowledge, this is one of the first studies to compare NSGA-II, PESA-II, and SPEA2 in Kansei engineering. We also sought to develop methods for the selection of representative solutions from a Pareto front for the visual presentation of an optimal product form.

This paper extends the application of MOEA in Kansei engineering. The contribution of this paper is that a HKES is constructed by combining the methodologies of SVR and MOEAs. To make a comparison, three typical MOEAs (NSGA-II, PESA-II, and SPEA2) were employed in HKES. In this study, SVR was utilized to build models for the prediction of affective responses. Using the trained SVR models as fitness functions, we employed MOEAs to search for optimal product forms. To obtain the typical form of a product, we utilized the fuzzy c-means algorithm (FCMA) to cluster the Pareto front into groups. We then compared the results of the three algorithms in order to discuss their application in the design of product form.

The remainder of this paper is organized as follows: Section 2 describes the background of HKES, prediction model, optimal design search model, and MOEA for product design. Section 3 provides an outline of the proposed HKES. Section 4 details the implementation procedures. Section 5 presents analysis of the experimental results. Finally, conclusions are drawn in Section 6.

2. Background review

2.1. Hybrid Kansei engineering system

HKES is an expert system used to facilitate the decision process for designer or consumers. HKES comprises a forward Kansei engineering system (FKES) and a backward Kansei engineering system (BKES). FKES is used to generate design alternatives as candidates for optimal design. BKES is used to predict the affective response to design alternatives. Soni et al. [12] applied neural network to the prediction of affective responses in BKES, and then used a genetic algorithm to identify optimal product designs in FKES. Yang [9] employed SVR as a predictive method in conjunction with NSGA-II as a method for optimization. Obviously, the core contents of HKES are the processes of prediction and optimization, in which predictive accuracy should be high and the optimal design should be the one best able to satisfy the needs of the user.

2.2. Model for prediction of affective responses

Affective response prediction is an important function of HKES for the evaluation of multiple alternatives. Prediction models can be categorized as linear or nonlinear. Commonly used linear models include quantification theory type I [13], multiple regression analysis [14], and conjoint analysis [15]. These methods can give an indication of the influence of various design elements on affective responses through the coefficients of independent variables, thereby facilitating the identification of important design elements. Unfortunately, the prediction accuracy tends to be low.

In many cases, the relationship between design elements and affective responses is not linear. This has prompted a number of researchers to adopt neural networks, which is a nonlinear method for the prediction of affective responses. However, neural networks require a large number of samples and suffer from poor generalizability, overfitting, and a tendency to fall into local optimum. A machine learning theory known as SVR has been gaining widespread application in nonlinear modeling applications. Scholars have applied SVR to product design, which resulted in high predictive accuracy and proved well-suited to the research of Kansei engineering [16].

Fuzzy logic has also been used to build “IF THEN” type rules to elucidate the relationship between design variables and affective responses [17]. These rules can also be used to predict the affective responses to a given design; however, prediction accuracy requires further improvement.

2.3. Search model for optimal product design

Optimization methods, such as genetic algorithms [13], ant colonies [18], and particle swarms [19] can be used to seek products capable of meeting specific affective responses. The affective responses of human to products often involve a number of aspects, which necessitates the ability to conduct searches based on multiple affective responses, which is essentially a multi-objective problem (MOP). However, previous researchers have tended to convert these MOPs into single-objective optimization problems through the use of linear weighting [3] or goal programming [4]. As a result, multi-objective optimization is not treated any differently than single-objective optimization. These methods are referred to as classical methods, which have demonstrated a wide range of applicability in many fields [20]. Unfortunately, classical methods require that users provide accurate information and only one solution is provided in each simulation run.

Multiple affective responses related to a product often conflict. This makes it difficult to find a solution capable of satisfying all of the