International Journal of Industrial Ergonomics 40 (2010) 237–246

Contents lists available at ScienceDirect

International Journal of Industrial Ergonomics

journal homepage: www.elsevier.com/locate/ergon

Product-form design model based on genetic algorithms

Shih-Wen Hsiao*, Fu-Yuan Chiu, Shu-Hong Lu

Department of Industrial Design, National Cheng Kung University, Tainan, Taiwan 70101, R.O.C

ARTICLE INFO

Article history:
Received 24 August 2008
Received in revised form
12 January 2010
Accepted 18 January 2010
Available online 2 March 2010

Keywords:
Genetic algorithms
Product design
Kansei Engineering
Morphological Analysis
Quantification Theory Type I Analytical Hierarchy Process

ABSTRACT

Industrial design attempts to enhance quality of life by designing products that meet consumer requirements. Combining concepts from various fields, including design, computer technology, aesthetics, and economics, industrial designers seek to improve quality of life by designing products that meet consumer needs. Industrial designers focus on customers' perceptions of products and their preferences for certain shapes, textures, colors, styles, linguistic variables, prices, and functions. Because new products are continuously being released, manufacturers must continually design products to satisfy customer needs to avoid displacement by market competitors. When planning strategies for marketing products to various users and consumers, managers must often consider multiple combinations of product shapes and must design products that cater to consumer tastes to minimize the risk of their products being rejected by the market. Companies with highly-skilled designers have more ideas, better and more competitive products, and shorter production times than companies with weak designers. This study analyzed product styles by applying genetic algorithms and Kansei Engineering Type II (AHP and Quantification Theory Type I). This research transforms the psychological conceptions of consumers into linguistic variables. A MATLAB program was constructed to enable designers to simulate consumer logic. The cognitive dissonance between virtual and real models was minimized by using a 3D CAD model, and the virtual model of optimum solutions in this study employed a rapid prototyping machine to generate real models efficiently. Future genetic algorithm models applying different decision theories may achieve even faster and more accurate results.

Relevance to industry: Component diversification enables rapid improvement in product competitiveness. This study proposes a support model that conforms to the psychological preferences of consumers by applying a genetic algorithm method. Therefore, the model is applicable to electronic commerce websites or to other unmanned shops.

1. Introduction

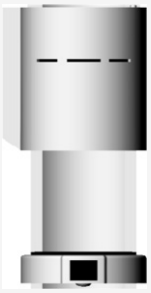
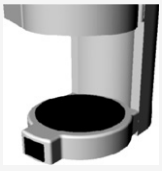
In today's fiercely competitive market, product design has already moved from the production-oriented approach applied in the past to a marketing-oriented approach, and finally to a customer-oriented approach. To minimize the risks and costs of new product development, product designers must consider factors such as old market tactics and investigation. The many factors considered in the course of product design include consumer preferences (Hong et al., 2008), manufacturing processes (Pine, 1993), color (Hsiao et al., 2008), texture (Chang, 2008), and interfaces (Artacho-Ramirez et al., 2008). The typical result involves substantial expenditures of time and money to optimize a design.

The many optimization methods discussed in the marketing literature include the neural network (NN) method, the support vector machine (SVM) method, and the genetic algorithm (GA) method. Precision and computing time are crucial to the effectiveness of a search methodology. The advantages of neural network method include their inherently slow search rate and their ability to obtain the partial minimum quickly, whereas SVM requires huge data sets and extensive personnel training. GAs are comparatively more effective at searching the entire solution space; therefore, they can be used to overcome the above shortcomings of the other two methods and improve efficiency in the data search process. GAs simulate the evolutionary processes of organisms in the natural world (Holland, 1992). Unlike other optimization methods, GAs do not perform random searches. When searching the next generation according to a specified criterion that can be applied to continuous or discontinuous cases, GAs usually

* Corresponding author.
E-mail address: swhsiao2002@yahoo.com.tw (S.-W. Hsiao).

0169-8141/$ – see front matter © 2010 Elsevier B.V. All rights reserved.
doi:10.1016/j.ergon.2010.01.009

Table 1
The items and categories in this case study.

3D model	Basic form components	Detailed form components	
		Items	
	A. Coffee marker 	Aa	a. Housing 
		Ab	b. Reservoir 
		Ac	c. Base 
	B. Carafe 	Ba	a. Carafe body 
		Bb	b. Carafe handle 

function according to the experience of the previous generation. Therefore, the GA method is applied in this study.

Biological organisms survive by ceaselessly adapting to environmental changes. They develop a genetic makeup that enables them to propagate according to the rules of crossover and mutation.

Fig. 1. The rules of gradation, subtraction, and addition.

Table 2
The 20 linguistic variables of the household appliances.

Elegant (17)*	Graceful (17)*	High tech (16)*	Applied (16)*	Creative (15)*
Rigid (15)*	Quality (15)*	Perceptual (14)	Concise (13)	Young (11)
Gentle (10)	Modern (9)	Smooth (8)	Lovable (7)	Individual (6)
Characteristic (6)	Popular (5)	Rational (5)	Domestic (3)	Symmetrical (2)

* The linguistic variable selected for use in this study

Additionally, because intra-species variation depends on mutation, these species are likely to survive for extended periods.

When a solution has many parameters that vary in a large range, and when data values are nonlinear or noncontiguous, genetic algorithms are advantageous for finding an optimum for the following four reasons:

(a) Parameters are calculated by coding rather by the algorithm.
(b) The search model is based on population rather than on a single point.
(c) Stochastic Searching of Direction (Payoff Function) – Genetic algorithms only require a fitness function and no other non-numerical auxiliary information.
(d) Searching is more efficient (Deterministic Rule) – Genetic algorithms are random and non-deterministic, so it is not necessary to define the range of the question.

In recent years, genetic algorithms have been applied in many fields. In the design field, for example, Beale (2007) constructed a data mining model that used genetic algorithms to measure the correlation between web pages and user interests. Hsiao and Tsai (2005) developed an automatic design system for rapidly obtaining a product form and its corresponding image by using fuzzy neural networks and genetic algorithms; Lampinen (2003) developed an approach using genetic algorithms for preliminary cam design and for subsequent shape optimization. Sevaux and Mineur (2007) applied genetic algorithms to fitting curves used in automotive body design; Saka (2003) used genetic algorithms to develop a method of optimizing the design of pitched roof steel frames with haunches for the rafters in the eaves; Carnahan and Redfern (1998) redesigned workplace furnishings to prevent job-related injuries caused by poor working environment design. In other fields, such as finance and economics, genetic algorithms have been used for investment forecasting, estimating the return on investments (Kim and Han, 2001), analyzing insolvency risk (Varetto, 1998), analyzing high technology industrial output (Wang and Hsu, 2008), and managing index fund portfolios (Oh et al., 2005). Engineers have also used genetic algorithms to design four-degree-of-freedom quarter car seats, suspensions (Gundogdu, 2007) and to develop design concepts such as the Computational Fluid Dynamics (CFD) evaluation mechanism (Ali et al., 2005; Lee, 2007), plastic injection molding (Babur and Tuncay, 2005), and a method for predicting minimum surface roughness (Hasan et al., 2006).

The data must first be quantized before it can be analyzed by genetic algorithms; the most popular quantization method in the product design field is Kansei Engineering (Nagamachi, 1995, 2002; Yang et al., 1999). The associated research and development processes, however, require combinations of other methods, such as Semantic Differential (Alcántara et al., 2005a,b; Hsiao and Huang, 2002), Quantification Type I Analysis (Llinares and Page, 2007; Tsuchiya et al., 1996), and Multidimensional Scaling Analysis (MDS) (Hsiao and Wang, 1998; Huang et al., 2007; Petiot and Yannou, 2004), to quantize the linguistic variables expressed by customers during product evaluations to develop design concepts and further the efficiency and accuracy of design decisions.

In this study, Kansei Engineering was used to quantize consumer responses to product styles. The feature data of each