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Case-Based Reasoning for Product Style Construction and Fuzzy Analytic Hierarchy Process Evaluation Modeling Using Consumers Linguistic Variables

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ABSTRACT Key form features are relative to the style of product, and the expression on style features depicts the product description and is a measurement of attribute knowledge. The uncertainty definition leads to an improved and effective product style retrieval when combined with fuzzy sets. First, a style knowledge and features database are constructed using fuzzy case-based reasoning technology; a similarity measurement method based on case-based reasoning and fuzzy model of the fuzzy proximity method may be defined by the fuzzy nearest-neighbor algorithm for obtaining the style knowledge extraction. Second, the linguistic variables (LV) are used to assess the product characteristics to establish the product style evaluation database for simplifying the style presentation and decreasing the computational complexity. Third, the model of product style feature set, extracted by fuzzy analytic hierarchy process (FAHP), and the final style related form features set are acquired using LV. This research involves a case study for extracting the key form features of the style of high heel shoes. The proposed algorithms are generated by calculating the weights of each component of high heel shoes using FAHP with LV. The case study and results established that the proposed method is feasible and effective for extracting the style of the product.

INDEX TERMS Artificial intelligent, knowledge based systems, machine learning algorithms, fuzzy logic, design methodology.

I. INTRODUCTION

The first task of creative product design is to consider creating an attractive style to meet the users needs. The product style is an important feature of creative design, a tangible material carrier of corporate brand value. It contains a wealth of social and cultural connotations. Many enterprises are committed to the pursuit of a unique and orderly style of creativity to shape the image of differentiated products, to significantly enhance the brand value of an enterprise, and to remove the vicious cycle of competition. Designers tend to form factors by using a design pattern to handle the same, or similar, shapes and colors of products in the creative design process. Therefore, through the study of the morphological parameters of a product itself, the style knowledge of the product can be obtained. In fact, the design process is a procedure of knowledge external transformation generated by the design knowledge through the designer's behavior. Knowledge acquisition of product style is a key dispute in modern industrial design. Design knowledge is a combination of the design experience, value and the background knowledge of production and users. According to the access methods variety, knowledge can be divided into "explicit knowledge" and "tacit knowledge". Scholars have focused on knowledge engineering, Artificial Intelligence (AI) and KANSEI engineering theory [1]–[3] for product design, such as mobile phones and auto design that inducted specialized knowledge acquisition research. These studies emphasize the subjectivity of the user and the use of statistical methods to achieve nearly subjective sensibility.

In addition, the design feature mapping can be performed to affective words using a reasoning model [4].

Product knowledge is a result of similar knowledge mapping and strategies to solve the design problem with similar background for specific design objects exist [5]. Design is a qualitative and quantitative process [6], [7], thus the product style design is based on knowledge/experience. In addition, the product design has the function of learning and self-strengthening. The design knowledge formed a representative style prototype in the process of long-term accumulation, expansion and evolution. As a kind of special type of design knowledge, the affective style knowledge acquisition attracts the focus of efficient design for several aspects including product, fashion and graphics [8], [9]. Typically, the traditional KANSEI engineering technique was used to map the relationship between the characterization of subjective image and feature modeling. Recently, AI has been used to solve style computation and knowledge acquisition research has made great progress [10]. Murai *et al.* [11] used association rules and Dempster-Shafer (D-S) evidence to extract knowledge from affective response. Wang and Nien [12] combined multiple correspondence analyses with association rule mining to discover the product design features. Kuroda and Hagiwara [13] introduced an image retrieval system which was the basis of product image generating research.

The coarse granularity knowledge itself and the style of the nonlinear calculations make the traditional treatment methods, such as obtaining quantitative and linear regression, unsuitable for the style of knowledge. Therefore, in the process of design knowledge expression, reasoning and acquisition, many scholars introduced AI, including: Neural Networks (NN) [14], [15], Case-Based Reasoning (CBR) [16], Fuzzy Logic [17], [18] as well as Expert Systems [19], [20]. Especially in the field of KANSEI Engineering AI has made significant progress. For example, Nagamachi [21], [22] used the attribute reduction theory of rough sets to extract the feature of the product of the corresponding KANSEI image. It also used the rough set and association rule [23], evidence theory [24], interactive genetic algorithm [25] and other techniques to obtain the specific shape of the perceptual image from the evaluation database. Based on the feature matching, the cognitive model of product style [26] was proposed, which made it possible to establish the style reasoning model through shape, color and other factors. Consequently, product form design is a relative of AI techniques and inference systems such as conditional evidence theory [27], decision making [28], CBR and data mining [29].

Typically, the complex problem of the analytic hierarchy process is a certain level of evaluation indicators. The consistency of the users thinking is difficult to guarantee. Thus, the Fuzzy Analytic Hierarchy Process (FAHP) combined with the advantages of the fuzzy method and the Analytic Hierarchy process (AHP) can be applied to extract the qualitative and quantitative characteristics of various evaluation factors. The fuzzy set is an extension of classical set theory, where the relationship between the element and the set is two kinds of relations, such as ‘‘belong to’’ and ‘‘not belong to’’. The relationship of elements in the fuzzy set theory has arranged a degree of membership. The new interval of any real use measures elements and a collection of relations; namely: each element represents a membership to describe the distance between the elements and sets.

In the traditional quantitative techniques, the variables are represented by data. A high degree of accuracy in the implementation is unnecessary in many of the basic operations performed by the people. The ability to deal with fuzzy sets technique and the resulting concentration information is one of the basic features of human intelligence. The ability to summarize information is often in the form of natural language. Linguistic variables are important aspects of natural language research. Also, the study of language variation will be an effective communication between people who can deal with fuzzy information.

The description of product style is generally based on the linguistic variable method. First, a variety of styles of the products with different degrees and high dimensional space of the product description are studied. Therefore, there is a need to study the style of semantic quantization with coarse granularity of knowledge description mechanism and to establish the expression system of linguistic variables based on the knowledge of style. Secondly, the product style classification reasoning model (classification of product style) is usually done by strict manual analysis and by experts on products shape, color, material and geometric connection features such as description and identification. Due to the product style information, fuzzy and the complicated structure, the artificial product style classification, the style prototype retrieval, huge workload and low accuracy are greatly influenced by subjective opinions of experts. This cannot effectively reflect the cognitive status of the users. Therefore, it is necessary to use the artificial evaluation method and machine reasoning. Third, an interactive evaluation and extraction system are proposed. The process of solving manual design (Fig. 1) including the ‘‘black box’’ process for product positioning style is not operable.

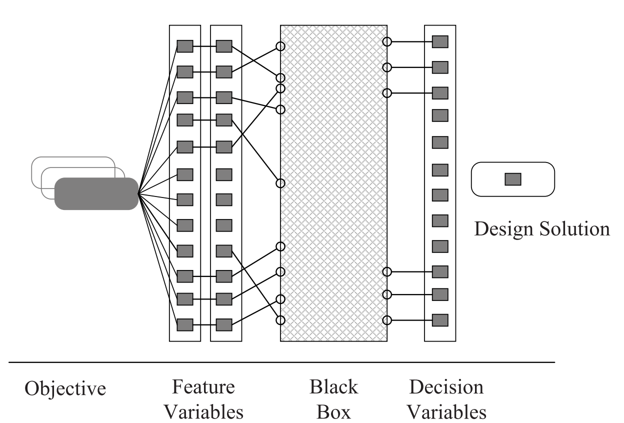

FIGURE 1. The process of design solutions.

Therefore, the establishment of automatic reasoning of product oriented style can overcome the black box. This creative designer provides a convenient and reliable fusion of subjective and objective evaluation technique. The formation mechanism of the automatic style extraction, knowledge assists designers to quickly determine the target customer group on the style of creative solutions the judge. The specific research framework is shown in Fig. 2.

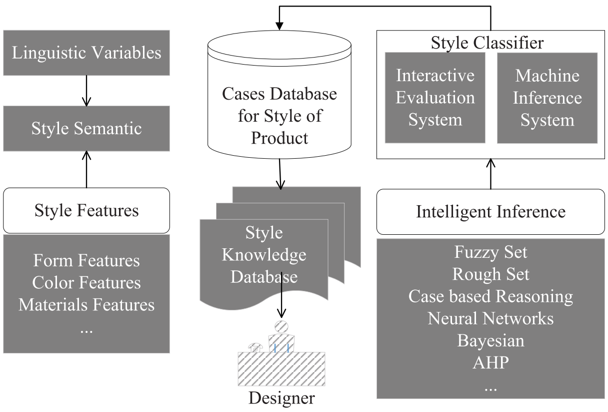

FIGURE 2. Framework for style extraction.

Linguistic Variables (LV) corresponding to numerical variables; however, the values of language variables are not numbers, but rather words or sentences. In general, words do not refund accurately, therefore the LV concept can provide an approximate characterization method to approximate the complex problems to define the phenomenon in a systematic means. The LV is employed to indicate the significance of one attribute relative to another one and LVs membership function. Consequently, in the current study, FAHP with fuzzy LV is proposed. The proposed approach applied the FAHP using linguistic variable in form design of high-heel shoe. The key form features are more helpful for design decision making and getting a quick response from the market.

In the current article, the style knowledge and features database are constructed by using fuzzy case based reasoning technology. The similarity definition is conducted by Fuzzy Nearest-Neighbor algorithm and style knowledge extraction was finished. In order to simplify the style presentation and decrease the computational complexity, linguistics variable scale is applied in both cases based reasoning and fuzzy analytic hierarchy process for product evaluation after constructing the style knowledge database. The final style related form features set is acquired using the linguistic variables and the case study showed the effectiveness of the proposed methods. The framework of the research is illustrated in Fig. 3.

The organization of the remaining sections is as follows. Section II introduces fuzzy case based reasoning that applied in product style extraction; Section III introduces the fuzzy analytic hierarchy process using linguistic variables for extracting product style. Section IV represents the case study on shoes style extraction of style knowledge database construction and form features extraction using the proposed

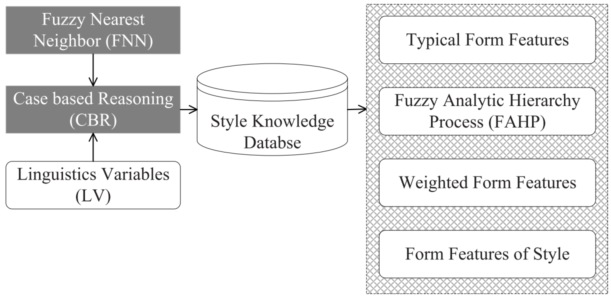

FIGURE 3. The framework of case-based reasoning for product style constructing and fuzzy analytic hierarchy process evaluation modeling using consumers linguistic variables.

methodology. Finally, Section V concludes the proposed work.

II. FUZZY CASE BASED REASONING

Fuzzy set [17] is an extension of classical set theory. In classical set theory, there are only two relations between the element and the set. The fuzzy relationship between the elements and the collection reflects a kind of membership degree. A relationship (any number of [0,1] interval) is used to measure the elements and set a definition of the membership degree of each element (Membership) to characterize the elements and set the distance. Due to the imprecision and uncertainty of the style knowledge expression, the introduction of fuzzy sets has played an important role. At the same time, some aspects of the product style formation (shape, material, color, craft), which are accumulated at the time of the results are closely linked with the previous products.

A. CASE-BASED REASONING

Case-based reasoning refers to the use of experience in decision-making of new cases and the use of an appropriate similarity definition in order to find a solution to the problem. In many situations, the previous case can be used to make further amendments to achieve the purpose of new problem decision. In 1980s, Roger Schank from Yale University was the first to propose the concept of case-based reasoning (CBR) [29]. Janet Kolodner and Michael Lebowitz developed the CBR as CYRUS [30] and IPP [31] respectively. In CBR research, case-retrieval is an important research direction. Eyke HÍźllermeier *et al.* [32] used the generalization of the similarity measure to improve case-based reasoning in the efficiency of case retrieval. The introduction of fuzzy sets makes the case-based reasoning even more powerful. Wu *et al.* [33] analyzed the problems arising from the application of fuzzy set theory to case-based reasoning and gave a solution. There are some scholars committed to the fuzzy clustering technology into the CBR that improved the performance of fuzzy.

The case-based reasoning is suitable for the formation of product style process due to the link between the case-oriented. In Conceptual Design (CD), T.Y. Slonima *et al.* [34] constructed a case database with 100 product attribute sets and constructed similarity measurement system based on

FCBR product creative design system. Case-based reasoning method has its unique advantages in industrial design field. It mainly uses a case to replace a rule; this makes the design knowledge representation and application, a method to accord with the mode of human thinking. In order to overcome the rule system, a single logical presentation to adapt to the well-defined issues such as clear weaknesses. In the process of CBR reasoning, the system only needs to adjust the relevant content according to the situation; the operation efficiency is high and the knowledge base is easy to set up which is more suitable for the extraction of the product style characteristic [35].

B. PROCESS OF CASE-BASED REASONING

In the current work, four actions, namely data retrieval, reuse, revise and retain are used in describing and using case-based reasoning. Data extraction refers to the extraction of the past, most similar cases from the database using the similarity definition, which is divided into neighborhood and induction algorithms. The neighboring method evaluates the similarity of a new case with the close degree in the previous case to judge. The inductive algorithm builds decision trees from the past cases and uses case rules to divide case clusters; each cluster contains a similar case. The method requires an identified target feature (i.e., the feature that the algorithm will summarize). Basically, the induction algorithm is used in a valid cluster-cluster-like case. Reuse is the use of similar case solutions to deal with the current problem. Furthermore, amendment means that if the past similar cases do not fully meet the current problems, the previous case can be amended based on the method. A reservation is a case in which a revised case is kept in the repository and becomes a new case. The CBR reasoning process is shown in Fig. 4.

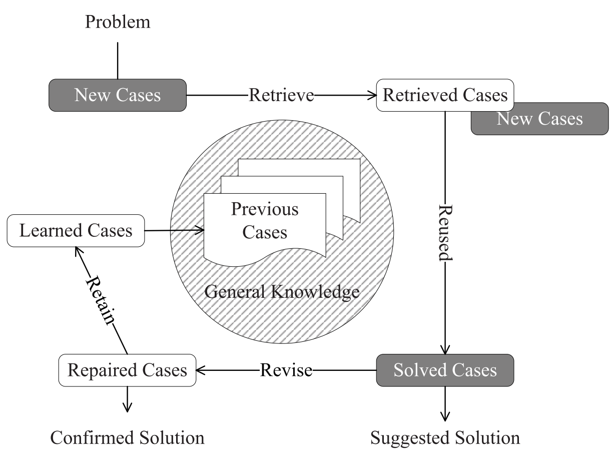

FIGURE 4. The process of CBR.

C. STYLE KNOWLEDGE EXTRACTION BY FUZZY NEAREST-NEIGHBOR TECHNOLOGY

Fuzzy logic has superior results in the expression of fuzzy language conditions, such as: very good, good, bad, very bad and so on. In fuzzy case-based reasoning, fuzzy similarity function (or preference) can be used to calculate the same attribute similarity to the target. The result of Fuzzy Preference Function is the Fuzzy Preference Vector (FPV) which contains the fuzzy preference value of each attribute and the vector values can be added by the concentration on the weight. The fuzzy preference function allows a comparison between certain properties and can be based on completely different scales.

The Nearest-Neighbor technology is a case-by-case comparison case. It compares the input case with the case attribute in the case base; it gives weight to the case attribute. Most case-based reasoning systems use this approach and the degree of similarity is usually normalized to a number between 0 and 1 (0 for completely different, 1 for the same), or as a percentage (100% represents exactly the same). However, the nearest neighbor method suffers from weak search efficiency when the case base grows to a certain scale or the case attribute is more.

In the current work, the fuzzy set theory is applied to describe the product style knowledge and to define the style membership degree of the product by the similarity of the product. However, in the acquisition of survey data, the description of product style attribute characteristics needs to be closer to the natural language approach. Therefore, the use of language variables (i.e. Linguistic Variables) is a viable method. Language variables are close to the natural language that can reflect the membership relationship between elements and collections. Table 1 shows the typical linguistic variables and their scales.

TABLE 1. Linguistic variables and scales.

Scale	1	2	3	4	5	6	7	8
Number of variables	2	3	5	5	6	7	9	11
N (None)								Y
VL (Very Low)			Y		Y	Y	Y	Y
L-VL (Low-Very Low)							Y	
L (Low)	Y	Y	Y	Y	Y	Y	Y	Y
FL (Fairy Low)				Y	Y		Y	Y
ML (Mol Low)						Y		Y
M (Medium)		Y	Y	Y		Y	Y	Y
MH (Mol High)						Y		Y
FH (Fairy High)				Y	Y			Y
H (High)	Y	Y	Y	Y	Y	Y	Y	Y
H-VH (High-Very High)							Y	
VH (Very High)			Y		Y	Y	Y	Y
E (Excellent)								Y

The membership function of linguistic variables is not linear, it is typically a non-linear curve. The specific value comes from the prior analysis of domain experts. Linguistic Variable [36]–[41] has been widely used in product evaluation domains especially in KANSEI engineering with FAHP techniques. Wang and Chen [42] applied fuzzy linguistic preference relations to the improvement of consistency of FAHP. Cables *et al.* [43] introduced an alternative to TOPSIS (a technique for order performance by similarity to ideal solution) decision-making approach for linguistic variables. Mezei *et al.* [44] aggregated linguistic expert knowledge in type-2 fuzzy ontologies. Liu and Jin [45] developed methods for aggregating intuitionistic uncertain linguistic variables and their application to group decision making. Combining with FAHP, linguistic variable proved its strong presentation ability [46], [47].

LV is defined as a quintuple $(K, T(K), U, G, M)$, where K is the name of a variable, $T(k)$ is term set of K identified as a collection of the language of k values name; U is relative to the base variable u, G is syntactic rule for generating the names of values of k; M is a semantic rule for relating its meaning for each k. In the current work, a specific term is considered referring to the name of a specific language value, denoted as $K1$. If $K1, K2, \cdots$ belongs to T, it can be formalized as $T = K1+K2+\cdots$. The linguistic variables are assigned to show the importance of one attribute relative to another attribute. Linguistic variables and their membership function are shown in Table 1. Fig. 5 illustrates the linguistic variables and their membership function.

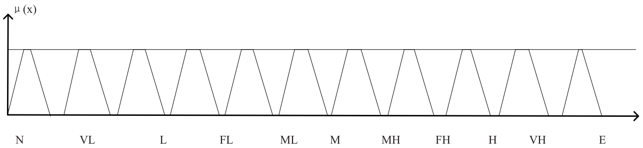

FIGURE 5. Linguistic variables and its membership function.

The fuzzy nearest neighbor method provides the information of the ambiguity by the case of the nearest neighbor. It can retrieve many cases whose similarity is greater than the threshold value and then sort the data to provide the decision maker with more auxiliary information to reduce decision errors. Searching for the nearest neighbor, each attribute in the same case may represent a different degree of importance. In order to find the most similar case in the case base more efficiently and accurately, the weight value should be assigned for each attribute. For the nearest neighbor method, the selected attribute weight value can be used to capture the case. However, the attribute value of the weight selection is a very difficult task. Traditionally, the definition of the weight value is determined by the experts according to their professional knowledge or experience.

D. FUZZY CASE-BASED REASONING FOR STYLE FEATURES DATABASE CONSTRUCTION

Definition 1: Cases can be formalized as a triple set: $Q = (P, w, V)$, where P denotes the name of cases, f denotes the cases weight in system, in FCBR, it is a defined membership, V is the value of the case.

Definition 2: For any case set C, $Style(C)$ denotes the style form features set of products.

Definition 3: For any case set C and a given case D, $Unstyle(C, D)$ denotes features in C but not in D, i.e., $unstyle(C, Q) = style(C) \backslash style(Q)$.

Definition 4: Let the attribute combination set Q^* is the extend set of Q, i.e.,$Q \subseteq Q^*$.

Fuzzy evaluation is necessary in this research for presentation formalization of attributes indispensable, and continuously.

Definition 5: The attribute description of C can be presented as:

$$f(style(C)) = \{\frac{c_1}{f_1} * w_1 + \frac{c_2}{f_2} * w_2 + \cdots + \frac{c_n}{f_n} * w_n\} \quad (1)$$

where, c_i is attribute feature of C, $f_i \in [0, 1]$ is fuzzy membership, and w_i is weight of attribute.

Definition 6: Let $Sim(C, D)$ be the similarity defined as

$$Sim(C, D) = \sum_{i=1}^{n} \|c_i - d_i\| \cdot w_i \quad (2)$$

where, $C = \{c_i | i = 1, 2, \cdots, n\}$, c_i is attribute feature of C. $D = \{d_i | i = 1, 2, \cdots, n\}$, d_i is attribute feature of D. $\|c_i - d_i\|$ is the distance between C and D defined by Definition 7.

Definition 7: The fuzzy presentation formalized distance between two case set is supposed $C = \{c_i | i = 1, 2, \cdots, n\}$ and $D = \{d_i | i = 1, 2, \cdots, n\}$ are the product set which have n form features, where C is known case and D is a new case, then we define a special distance.

$$fsim(C, D) = [\sum_{i=1}^{n} |f_i w_i - g_i u_i|^p]^{\frac{1}{p}} \quad (3)$$

i.e. weighted fuzzy membership based *Mincowsky* distance.

Definition 8: For the average case computing of style database, let case database be $\Omega = \{C_i | i = 1, 2, \cdots\}$, $\sum f$ be the sum of membership, $Card(\Omega)$ be the number of case record; $Max\{C_i\}$ be the high frequency cases i-th features, w_{ij} be the weight of the j-th case in the i-th class, then the average case computing is,

$$\begin{aligned} Aver(\Omega) = \{ & \frac{Max\{c_1\}}{\sum f / Card(\Omega)} \cdot \sum_{i=1}^{Card(\Omega)} w_{1i} \\ & + \frac{Max\{c_2\}}{\sum f / Card(\Omega)} \cdot \sum_{i=1}^{Card(\Omega)} w_{2i} + \ldots \\ & + \frac{Max\{c_n\}}{\sum f / Card(\Omega)} \cdot \sum_{i=1}^{Card(\Omega)} w_{ni}\} \end{aligned} \quad (4)$$

Definition 9: Similarity computing of new case and case database:

(1) if the system uses new case and average case, then the equation (4) can be adopted.

(2) if the system used new case and each previous case first and averages hereafter, then:

$$sim = \frac{1}{Card(\Omega)} \sum_{i=1}^{Card(\Omega)} f \cdot sim(C_i, D), \forall C \in \Omega \quad (5)$$

Definition 10: For new case D and using the definition (9), if the similarity is less than a given threshold δ, then $\Omega^* = \Omega \cup D$, Ω^* is an extended set of Ω that is new case database, i.e., new case D is reserved.

The pseudo-code of FCBR is presented in Algorithm 1.

Algorithm 1 Fuzzy Case Based Reasoning in Style Knowledge Retrieval

Require: m: degree of distance to membership
Require: c: number of class
Ensure: u: $u_i(x) = \frac{1}{\sum_{j=1}^{c}(1/\|x-z_j\|^{\frac{2}{m-1}})} \cdot \frac{1}{\|x-z_i\|^{\frac{2}{m-1}}}$

```
‖x − z_j‖: x's membership to class Z_j
W ← [Z_1, Z_2, ··· , Z_c] // the number of features
INPUT X vector of style
1 ← i
while 1 do
    //calculate the distance of X and each class
    Compute sim(Z_i, X)
    i ← i + 1
    if i = c then
        Break
    end if
end while
j = 1
while 1 do
    //calculate membership of X and each class
    Compute u_i(Z_i, X)
    i ← i + 1
    if i = c then
        Break
    end if
end while
```

In the new case set $\{D_k, k = 1, 2, \cdots\}$, if there exists a corresponding feature distance and the average case is greater than a given threshold value, the system can modify the membership of the average case corresponding to the property, in order to achieve a reasonable evaluation of the subsequent case. The case reasoning system is then constructed. Through this kind of case library, a reasonable evaluation can be performed of the subsequent cases in order to achieve the final formation of style.

III. FUZZY ANALYTIC HIERARCHY PROCESS USING LINGUISTIC VARIABLES

A. PRODUCT STYLE MODEL BASED ON KANSEI ENGINEERING

It is concluded that the product style information is based on the form features and the mental image [48]. Form feature information is the materialized form that can be seen, including the form, texture and color. The image feature information is peoples psychological feeling of products, such as strong or frivolous, balanced or upset and smooth or rough [49]–[51]. People always use a series of abstract image semantics to describe all sorts of subjective feeling. Furthermore, the cognitive psychology research shows that image semantics are an effective means of description and measurement of some tacit knowledge.

1) ANALYSIS ON STYLE OF PRODUCT FORM

Product design is the process of coding all relative elements of the product through the designer's emotional integration and practical functions. The combination of technologies has obvious characteristics, so that it can be well recognized by people [52], [53]. Style is consisting of similar form, color, material and other elements of the design. Several design techniques that involve the style features can use the cognitive mechanism as the basis through morphological analysis. It may be the form of the same product style that is divided into several independent attribute form unit and different form attribute units belonging to different form attribute class. Express the style features set by:

$$X = \{X_1, X_2, \cdots, X_n\} \tag{6}$$

The i-th matrix of form features is given by:

$$X_i = \{X_{i1}, X_{i2}, \cdots, X_{in}\} \tag{7}$$

2) EXTRACTING IMAGE OF PRODUCT

Identification and classification of similar products are the main process for style cognition; the process of the individual experience and psychological structure comparison. People usually use natural language expressions, such as the common "concise", "fashion" and other linguistic expressions in terms of modeling features of the products to make subjective evaluation. Different styles of products belonging to a certain style system of image semantic space. KANSEI engineering based image semantics extraction methods can be employed to obtain recessive stylistic knowledge. It is one of the effective means that includes two steps: i) collect the image semantic through the system using an open questionnaire survey. Semantic selection requires the products covered adjectives of semantic cognitive space. ii) Select the image semantic under preliminary screening, and then the selected image semantics and some style sample image evaluation are tested by using a Likert scale. Finally, the factor analysis results are taken to select several representative image semantic factors from the axis of the evaluation test. A style description of space image semantic set can be given by:

$$D = \{d_1, d_2, \cdots, d_m\}. \tag{8}$$

3) WEB-BASED EVALUATION SYSTEM FOR THE PRODUCTS STYLE

The web-based product style information evaluation system was carried out to obtain the style of cognitive information. This system includes an online questionnaire investigation using XML (Extensible Markup Language) data storage and a variety of methods for data analysis, mining and finally collected the product style information. The main functions of product style information collection system are consistent of three steps as follows.

Step 1: Use the Likert scale method to carry out the assessment method for the cognitive style image semantic through scaling responses of the survey through the importing sample images of the style and KANSEI image semantics.

Step 2: Perform cluster analysis, principal component analysis and other data analysis techniques for the various stages of the survey and providing the corresponding data processing.

Step 3: Generate the formation of style information, decision table based on the analysis of the results of the data.

B. FUZZY ANALYTIC HIERARCHY PROCESS FOR PRODUCT DESIGN EVALUATION

Analytic Hierarchy Process (AHP) is a method to extract qualitative and quantitative phase of processing characteristics of various evaluation factors. Since people's subjective judgment process is mathematical, the decision basis is easy to be accepted and this is more suitable for the complex social science domain. The AHP theory is complete, rigorous in structure and concise in the problem solution. It has obvious advantages in solving non-structured decision problem. The fuzzy set [54] plays an imperative role in several industrial applications due to the non-precision and uncertainty of the knowledge expression [55]–[58]. It also generates some technical innovation issues combining with controller design [59]and modeling [60], especially in product style extraction and evaluation [61]. The basic ideas and steps of the fuzzy analytic hierarchy process are basically consistent with the steps of AHP with the following differences:

- The establishment of the judgment matrix is different: in the AHP, it makes comparison of two elements to establish a consistent matrix [62]; while in the FAHP, it performs the comparison of the elements to establish a fuzzy consistent judgment matrix.
- The weight of the relative significance of each element in the matrix is different.

The FAHP improved the problems existing in the traditional analytic hierarchy process and improved the reliability of the decision. It has two forms of fuzzy number-based and fuzzy consistency matrix-based [63]. de Graan [64] proposed a triangular fuzzy number to express views among the two elements, and then calculate the fuzzy weights of all criteria for decision-making. Laarhoven and Pedrycz [65] developed a Triangular Fuzzy Number (TFN) algorithm instead of the level analysis method in pair-wise comparison of definite values with fuzzy weight calculation of the standards on the number of least square method. Buckley [66] proposed a trapezoidal fuzzy number to express the relative important degree method of two elements and the formation of the fuzzy positive reciprocal matrix. Afterward, the method of geometric average number was carried out to calculate the fuzzy weight of each fuzzy matrix.

Finally, the alternative fuzzy weights are a priority area to set the graphics function between rows of alternatives. Chou *et al.* [67] introduced a number of letters to represent the competitions between each criterion values. Afterward, each factor of fuzzy comprehensive range of values was calculated for analysis. Two of two factors of each unit through regularization were calculated for each element of the non-fuzzy value (non-fuzzy value). In the FAHP for product style extraction, the alternatives and the significant attributes product were identified. For each attribute and each pair of alternatives, the decision makers specify their preference in the form of a fraction between 1 and 9. Decision makers similarly indicate the relative significance of the attributes. Each matrix of preferences was evaluated by using eigenvalues to check the consistency of the responses. This produces a ''consistency coefficient'', where a value of ''1'' means that all preferences are internally consistent. This value would be lower, if a decision maker said that X is preferred to Y, Y to Z but Z is preferred to X (such a position is internally inconsistent). It is this step that causes many users believe that FAHP is theoretically well founded. A score is calculated for each alternative. The fuzzy analytic hierarchy process includes the following steps: i) establish a hierarchical analysis framework, ii) establish a pair-wise comparison matrix, iii) establish the triangular fuzzy number, iv) establish the fuzzy positive reciprocal matrix, v) establish the fuzzy weight of fuzzy positive matrix, vi) check the consistency of fuzzy matrix, vii) calculate the A-cut value, viii) establish a solution model, regularization and level series and ix) sort the factors in consistent with the calculated weights. The two basic steps in the process are to model the problem as a hierarchy, then to establish priorities for its elements. These are more fully described below.

Let the universe set U denoted by $u = \{u_1, u_2, \cdots, u_p\}$ and the evaluation level be $v = \{v_1, v_2, .., v_p\}$, each level relative to a fuzzy subset. Consequently, in the current work the steps are as follows:

Step 1: Establish the fuzzy relation matrix to calculate the fuzzy membership of each index for the evaluation object $(S|u_i)$ and to continue in order to obtain the fuzzy relationship matrix as:

$$S|_U = \begin{bmatrix} S| & u_1 \\ S| & u_2 \\ & \cdots \\ S| & u_p \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ r_{p1} & r_{p2} & \cdots & r_{pm} \end{bmatrix} \tag{9}$$

Instead of using one factor for the evaluation, the fuzzy factors evaluation requires more information from the matrix [50].

Step 2: Calculate the factors weights, where $A = (a_1, a_2, \cdots\cdots, a_p)$ is the weight vector having the element a_i in A to represent the membership of factor u_i. In a multi-level evaluation process, analytic hierarchy was used in order to sort the significance of factors and to decide the weights. The normal weights are given by:

$$\sum_{i=1}^{p} a_i = 1, a_i \geq 0, i = 1, 2, \cdots, n \tag{10}$$

Step 3: Result vector calculation In order to obtain the fuzzy evaluation matrix B, the multiple A and R using given operator are to be used as follows:

$$A \cdot R = (a_1, a_2, \cdots, a_p) \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ r_{p1} & r_{p2} & \cdots & r_{pm} \end{bmatrix} = (b_1, b_2, \cdots, b_m) = B \tag{11}$$

Step 4: Determining the weights using the following steps:

- Determine the objectives and evaluate the factors. Let objects evaluation index be: $u = \{u_1, u_2, \cdots\cdots, u_p\}$.
- Structure the judgment matrix. The matrix elements value reflects the understanding of the relative importance of each element. The scale ranges of $1 - 9$ and its reciprocal are generally used. However, when the mutual comparison factors importance can be explained with the actual meaning of the ratio, the value of the corresponding matrix elements is to use this ratio in order to obtain the judgment matrix.
- Calculate the judgment matrix. Mathematical software is used to calculate the maximum eigenvalue of the matrix and its corresponding feature vector. The feature vector is the importance of the evaluation factors, which is the distribution of weight coefficient. Afterward, the maximal eigenvalue $\lambda_{\max}$ of S and the eigenvector A are calculated. The eigenvector A is the weight distribution.
- Set the consistency index $CI = \frac{\lambda_{\max}-n}{n-1}$, and the average consistency random index to perform the consistency test. In order to check the consistency of the judgment matrix, the consistency index and the average random consistency index are calculated. The construction method is random with the standard and their reciprocal fill sample matrix of the upper triangular various, the main diagonal of the value is always 1, corresponding to transpose position is used the reciprocal of the corresponding position of the random number. Then, the consistency index values of each random sample matrix are calculated. In addition, the average of these values is obtained using the average random consistency index value. When the random consistency rates $CR = CI/RI < 0.10$, i.e. sorting results are satisfactory consistency and the weight coefficient distribution is reasonable. Otherwise, it is necessary to adjust the judgment matrix element values to redistribute weight coefficient values. Though, the random consistency ratio is to adjust the value judgment matrix elements of redistribution of weight coefficient values. The algorithm of weight matrix computing and consistent judgment is illustrated bellow.

Algorithm 2 Get Wight Matrix

Require: $A \leftarrow input$
Ensure: w
  // Normalize the preference matrix
  for $iPreference = 1$ to $length(A)$ **do**
    $B(:, iPreference) \leftarrow A(:, iPreference)/sum(A(:, iPreference))$
  end for
  //Computer the weight matrix
  for $iPreference = 1$ to $length(B)$ **do**
    $W(iPreference) = mean(B(iPreference, :))$
  end for
  $W \leftarrow W'$
  $output \leftarrow W$

Algorithm 3 Consistent Check

Require: $A \leftarrow input$
Ensure: $W \leftarrow getWeightMatrix(input)$
  //Get Weight Matrix
  $AW \leftarrow A * W$;
  //Find the value of α
  $\alpha \leftarrow 0$;
  for $iPreference = 1$ to $length(A)$ **do**
    $\alpha \leftarrow \alpha + (AW(iPreference)/W(iPreference))$
  end for
  $\alpha \leftarrow \alpha/length(A)$
  //COMPUTE CONSISTENCY INDEX
  $n \leftarrow length(A)$
  $CI \leftarrow (alpha - n)/(n-1)$
  $RI \leftarrow [r_{11}, r_{12}, \cdots]$
  // Populate the RI matrix
  CHECK FOR RATIO
  if $((CI/RI(n)) < 0.1)$ **then**
    $returnValue \leftarrow 1$
  else
    $returnValue \leftarrow 0$
  end if
  $output \leftarrow returnValue$

IV. CASE STUDIES

A. CASES CONSTRUCTION

In linguistics, an adjective is a describing word and the main syntactic role that qualifies a noun or noun phrase, giving more information about the object signified. A given occurrence of an adjective can generally be classified into one of three kinds of use for attributive, predicative and nominal adjectives. Design is a process of accumulation; the designer should set up a huge Gallery for various styles. Some of the product style adjectives can be retrieved using the style image survey system. Adjectives for style evaluation were shown in Table 2, marked by X if there has a style description of a given product.

B. FUZZY CASE BASED REASONING

In CBR experiments, the most important work is to find examples in case-based reasoning, the input cases are to be classified correctly with appropriate weight values. The relatively simple method is given directly by the

TABLE 2. Style evaluation table using adjectives.

Adjectives	Warm	Vitality	Varied	Lucky	Interest
Optimistic					
Dynamic			X		
Stimulate			X	X	
Sexy		X			X
Fierce					X
Aggressive				X	X
Powerful Function					
Vitality				X	
Grace		X	X		
Rich	X			X	X
Mature					
Heal			X		
Peace	X			X	X
Wisdom					
Chill					
Protect					
Security			X		
Loyal				X	X
Natural					X
Lucky				X	
Hope	X				
Success					
Generous					
Romantic					
Soft		X	X		
Subtle				X	
Sweet			X		
Friendly	X				
Hot				X	
Perceptual		X			
Bright					X

FIGURE 6. Typical cases in the system list by using FCBR.

TABLE 3. Style description, presented product and features code by fcbr process.

Style Semantic	Product code	Feature Code
Classical	F_11	C[1,3,2,6,10,11,2,12,8]
Aristocratic	F_13	C[2,3,12,10,9,11,2,10,8]
Rock	F_14	C[4,2,5,8,10,9,1,1,8]
Dynamic black	F_22	C[4,10,2,6,10,7,2,7,8]
Love	F_23	C[6,3,2,6,10,11,2,1,8]
Metal	F_24	C[1,4,5,6,1,4,2,7,8]
Classic Nordic	F_31	C[2,4,2,6,3,2,2,6,7]
Bohemia	F_33	C[11,3,2,6,10,1,2,7,9]
Luxury	F_41	C[12,2,3,6,4,11,1,7,2]
Retro	F_42	C[10,7,1,5,10,4,2,7,8]
Electronics	F_43	C[2,7,2,6,11,3,2,7,3]
Simple Business	F_53	C[7,6,2,5,10,12,2,2,7]
Fashion Modern	F_54	C[1,9,1,6,10,9,1,2,3]
Transformation Movement	F_55	C[1,3,2,6,10,11,2,7,8]

domain experts according to the professional knowledge. However, the weight distribution is not accurate due to the subjective deviation. Therefore, this case is constructed and to be reallocated by two parts, one was experts evaluation and the second part is to carry out a survey, the statistical analysis to get the weight value, and then by experts and the questionnaire combined with the two. 328 questionnaires were completed, combined with expert evaluation, and 20 typical cases relative to style database as shown in Fig. 6 were aquired.

In the current work, the cases database is constructed using product form features and let $F = [FORM\_ij]_{4\times 5}$ be the form matrix. By using FCBR, the key form features shown in Fig. 7 were constructed. The style product (high heel shoes) was coded in 9 features and 12 typical cases were added to the database by using FCBR. So, there are 108 features in feature database.

Table 3 illustrates the style description as well as the presented product and features code by FCBR process.

An applied application for the proposed approach using the FAHP and the LV variable for form design of the high-heel shoe to extract key form features relative the style is involved. The style extraction of high heel shoes will be more helpful for design decision making and getting quick response of the market. Some scholars focused on the support system of shoe design. Shieh and Yeh [68] developed a design support system for the exterior form of running shoes using partial least squares and neural networks. Butdee [69] introduced a hybrid feature modeling for sport shoe sole design. Furthermore, some researches focused on designing a comfortable high heel shoes system [70], [71]. In the current work, in order to obtain the main components of the high heel shoe, a randomly distributed questionnaire system was carried out independently. From the 100 dispersed surveys, 89 were returned, resulting in a return rate of 89%; 83 forms were validated; the validation rate was 93.2%. Finally, nine main components are obtained as shown in Fig. 8 (marked with numbers from 1 to 9). In addition, the high heel shoes are divided into 12 categories for each component. Figure 7 listed totally 108 form features.

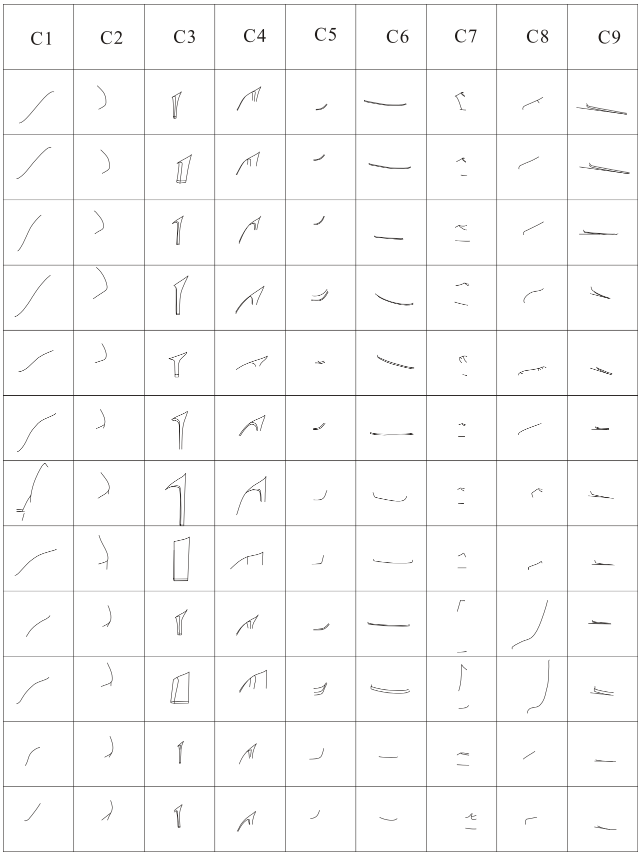

FIGURE 7. The 108 form features of high heel shoe relative to style knowledge record.

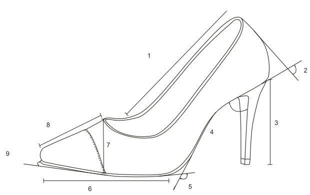

FIGURE 8. The nine main components of high heel shoes.

TABLE 4. Quantitative evaluation of grading standards.

Score	Evaluation by LV	Level
$x_i > 9.5$	Very Good	E1
$8.5 < x_i < 9.5$	Good	E2
$7.5 < x_i < 8.5$	Median	E3
$6.5 < x_i < 7.5$	Normal	E4
$5.5 < x_i < 6.5$	Bad	E5
$x_i < 5.5$	Very Bad	E6

C. RESULTS AND DISCUSSION

The evaluation and the score interval for the levels are assigned using the survey data obtained by the scoring system as shown in Table 4.

Using the survey data, the fuzzy comprehensive evaluation was applied to calculate weights of 2 levels using as depicted in Table 5.

TABLE 5. Two level evaluation factors and their weighting.

Components	Features	Weights by FAHP
C1	C1_1	0.103
0.212	C1_2	0.101
	C1_3	0.288
	C1_4	0.123
	C1_5	0.212
	C1_6	0.178
	C1_7	0.288
	C1_8	0.136
	C1_9	0.112
	C1_10	0.145
	C1_11	0.211
	C1_12	0.115
C2	C2_1	0.213
0.204	C2_2	0.123
	C2_3	0.132
	C2_4	0.225
	C2_5	0.210
	C2_6	0.211
	C2_7	0.303
	C2_8	0.129
	C2_9	0.287
	C2_10	0.231
	C2_11	0.123
	C2_12	0.189
...	...	...
C9	C9_1	0.111
0.178	C9_2	0.113
	C9_3	0.222
	C9_4	0.231
	C9_5	0.121
	C9_6	0.214
	C9_7	0.231
	C9_8	0.121
	C9_9	0.221
	C9_10	0.221
	C9_11	0.234
	C9_12	0.143

The results obtained in Table 5 established that the weights of the first and second hierarchy are used to calculate the overall weighted features of the product and the following steps are used to attain each factors weight:

Step 1: Determine the evaluation object set: $C =$ high heel shoes.

Step 2: Structural evaluation factors set: $u = \{u_1, u_2, \cdots, u_9\} = \{C1 \cdots, C9\}$.

Step 3: Determine the domain level reviews: $v = \{v_1, v_2, \cdots, v_6\} =$ {Very Good, Good, Median, Normal, Bad, Very Bad}.

Step 4: Calculating the weight for the first level index and constructing judgment matrix of six factors ($S = U_{ij}$) are as follows:

$$\begin{bmatrix} 1 & 4/3 & 5/4 & 1 & 9/5 & 6/5 \\ 3/4 & 1 & 9/10 & 8/9 & 7/5 & 8/9 \\ 4/5 & 10/9 & 1 & 4/5 & 3/2 & 1 \\ 1 & 9/8 & 5/4 & 1 & 2 & 5/4 \\ 5/9 & 5/7 & 2/3 & 1/2 & 1 & 4/6 \\ 5/6 & 9/8 & 1 & 4/5 & 6/4 & 1 \end{bmatrix} \tag{12}$$

The form features and their weights, which describe the style of shoe, can be presented as a fuzzy set as:

$$
\begin{aligned}
E = {} & \frac{v(C1\_2)}{0.1491} + \frac{v(C2\_3)}{0.1129} + \frac{v(C3\_10)}{0.2130} + \frac{v(C4\_7)}{0.2212} \\
& + \ldots \frac{v(C5\_3)}{0.2561} + \frac{v(C6\_6)}{0.1127} + \frac{v(C7\_2)}{0.2110} \\
& + \frac{v(C8\_11)}{0.2220} + \frac{v(C9\_5)}{0.1212} \qquad (13)
\end{aligned}
$$

Consequently, the style features are obtained as shown in Fig. 9.

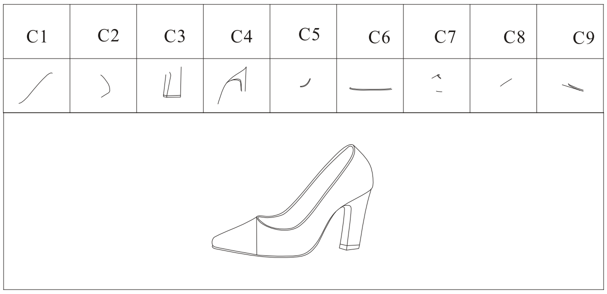

FIGURE 9. **The key form feature of a certain high heel shoes for style extraction.**

The preceding results established the attained key form features and composed them as a product using the proposed method. Thus, as a future work, the entire features must be collected widely and each fuzzy linguistic variable interval has to be improved. In addition, a large-scale case database can be designed to study more reasonable definition of similarity measure, to improve the weight assignment scheme as well as the reasoning mechanism and to carry out deep excavation and further research from modeling, color and material. Furthermore, in the case study, this model proved to be effective, however there some issues, namely i) the size of the case base is not large and the morphological feature weight in the style similarity measure also depends on the expert's subjective consciousness and ii) in addition to styling and color, materials and connection relations described in this paper, there are other factors in the attributes describing the style characteristics, such as the use of function, brand recognition and emotional experience. Therefore, the extraction of style knowledge can be applied to further development.

V. CONCLUSIONS

In this paper, the formation of style knowledge, reasoning and expression were introduced due to the uncertainty of style knowledge. Based on design thinking process, fuzzy case-based reasoning methods were used to overcome the shortcomings of single and linear. The linguistic variables are used to describe the style of knowledge to make it more conform to the cognitive style of knowledge. The key form features were extracted by using a fuzzy analytic hierarchy process with fuzzy linguistic variables. The current work developed the algorithm for extracting the style of product. Applying fuzzy evaluation provided more effective results than the traditional KANSEI method. However, in this work, the linguistic variables were used to evaluate the key product form. The experimental results established by the case study showed a feasible research direction for product style research using a fuzzy analytic hierarchy process with fuzzy linguistic variables.

REFERENCES

[1] S. Baek, M. Hwang, H. Chung, and P. Kim, "Kansei factor space classified by information for Kansei image modeling," *Appl. Math. Comput.*, vol. 205, no. 2, pp. 874–882, 2008.
[2] B. B. Nadia, "Kansei-mining: Identifying visual impressions as patterns in images," in *Proc.-Joint 9th IFSA World Congr. 20th NAFIPS Int. Conf.*, 2001, pp. 2183–2188.
[3] O. Koji, Y. Matsubara, and N. Ueno, "Extraction of relationship among Kansei words by expert system using rough set analysis," in *Proc. Int. Conf. Active Media Technol.*, 2005, pp. 461–466.
[4] J. R. Chou, "A Kansei evaluation approach based on the technique of computing with words," *Adv. Eng. Informat.*, vol. 30, no. 1, pp. 1–15, 2016.
[5] C. C. Yang, "Constructing a hybrid Kansei engineering system based on multiple affective responses: Application to product form design," *Comput. Ind. Eng.*, vol. 60, no. 4, pp. 760–768, 2011.
[6] C. C. Li, Y. Dong, F. Herrera, E. Herrera-Viedma, and L. Martínez, "Personalized individual semantics in computing with words for supporting linguistic group decision making. An application on consensus reaching," *Inf. Fusion*, vol. 33, pp. 29–40, Jan. 2017.
[7] L. Malatesta, S. Asteriadis, G. Caridakis, A. Vasalou, and K. Karpouzis, "Associating gesture expressivity with affective representations," *Eng. Appl. Artif. Intell.*, vol. 51, pp. 124–135, May 2016.
[8] S. Duo and L. X. Song, "An E-learning system based on affective computing," *Phys. Proc.*, vol. 24, pp. 1893–1898, Jan. 2012.
[9] L. Bozhkov *et al.*, "EEG-based subject independent affective computing models," in *Proc. Comput. Sci.*, vol. 53, Aug. 2015, pp. 375–382.
[10] A. Vlachostergiou, G. Caridakis, and S. Kollias, "Investigating context awareness of affective computing systems: A critical approach," in *Proc. Comput. Sci.*, vol. 39. 2014, pp. 91–98.
[11] M. Tetsuya, K. Yasuo, and S. Yoshiharu, "Association rules and dempster-of evidence," *Lecture Notes in Artificial Intelligence*. Berlin, Germany: Springer-Verlag, 2008, pp. 377–384.
[12] C. H. Wang and S. H. Nien, "Combining multiple correspondence analysis with association rule mining to conduct user-driven product design of wearable devices," *Comput. Standards Interfaces*, vol. 45, pp. 37–44, Mar. 2016.
[13] K. Kazuhiro and H. Masafumi, "An image retrieval system by impression words and specific object names-IRIS," *Neurocomputing*, vol. 43, pp. 259–276, Jun. 2002.
[14] W. Bernard, E. P. David, and A. L. Michael, "Neural networks: Applications in industry, business and science," *Commun. ACM*, vol. 37, no. 3, pp. 93–105, Mar. 2017.
[15] Z. Xu, "A study of computer aided form design for product style," Ph.D. dissertation, Northwest Polytech. Univ., Fremont, CA, USA, 2010.
[16] M. L. Maher and A. Gomez de Silva Garza, "Case-based reasoning in design," *IEEE Expert*, vol. 12, no. 2, pp. 34–41, Apr. 1997.
[17] L. A. Zadeh, "Fuzzy sets," *Inf. Control*, vol. 8, no. 3, pp. 338–353, Jun. 1965.
[18] H. Liu, "Using fuzzy association rule algorithms to enhance new product development," M.S. thesis, Dept. Ind. Eng. Manag., Yuan-Ze University, Taipei, Taiwan, 1980.
[19] R. Forsyth, *Expert Systems: Principles and Case Studies*, 2nd ed. London, U.K.: Chapman & Hall, 1989.
[20] E. K. Robert, *Computational Intelligence in Control Engineering*. New York, NY, USA: Marcel Decker, 2005.
[21] N. Mitsuo, "Kansei engineering and comfort," *Int. J. Ind. Ergon.*, vol. 19, no. 2, pp. 79–80, 1997.
[22] N. Mitsuo, "Kansei engineering as a powerful consumer-oriented technology for product development," *Appl. Ergon.*, vol. 33, no. 3, p. 289 294, 2002.
[23] F. Shi, S. Sun, and J. Xu, "Association rule mining of Kansei knowledge based on rough set," *Comput. Integr. Manuf. Syst.*, vol. 14, no. 2, pp. 407–411, 2008.
[24] F. Shi, S. Sun, and J. Xu, "Fuzzy dempster-Shafer evidence theory and its application to product Kansei evaluation system," *J. Comput. Aided Design Comput. Graph.*, vol. 20, no. 3, pp. 361–365, 2009.

[25] J. Xu and S. Sun, "Product form design based on orthogonal interactive genetic algorithm," *Comput. Integr. Manuf. Syst.*, vol. 13, no. 8, pp. 1470–1475, 2007.

[26] Q. Huang and S. Sun, "State-of-the-art of Research on Product Style Computation," *J. Comput. Aided Design Comput. Graph.*, vol. 18, no. 11, pp. 1629–1636, Nov. 2006.

[27] L. A. Zadeh, "The concept of a linguistic variable and its application to approximate reasoning—I," *Inf. Sci.*, vol. 8, no. 3, pp. 199–251, 1975.

[28] L. A. Zadeh, "Linguistic variables, approximate reasoning and dispositions," *Informat. Health Soc. Care*, vol. 8, no. 3, pp. 173–186, 1983.

[29] S. Roger, *Dynamic Memory: A Theory of Learning in Computers and People*. New York, NY, USA: Cambridge Univ. Press, 1982.

[30] K. Janet, "Reconstructive memory: A computer model," *Cognit. Sci.*, vol. 7, pp. 281–328, Mar. 1983.

[31] L. Michael, "Memory-Based Parsing," *Artif. Intell.*, vol. 21, pp. 363–404, Jun. 1983.

[32] H. Eyke *et al.*, "Supporting case-based retrieval by similarity skylines: Basic concepts and extensions," in *Lecture Notes in Computer Science*, K.-D. Althoff, Eds., Trier, Germany, Springer: 2008, pp. 240–254.

[33] M. C. Wu, Y. F. Lo, and S. H. Hsu, "A fuzzy CBR technique for generating product ideas," *Expert Syst. Appl.*, vol. 34, no. 1, pp. 530–540, 2008.

[34] T. Y. Slonima and M. Schneider, "Design issues in fuzzy case-based reasoning," *Fuzzy Sets Syst.*, vol. 117, pp. 251–267, Jan. 2001.

[35] I. Watson, "Case-based reasoning is a methodology not a technology," *Knowl.-Based Syst.*, vol. 12, no. 5, pp. 303–308, 1999.

[36] P. Liu, "Some geometric aggregation operators based on interval intuitionistic uncertain linguistic variables and their application to group decision making," *Appl. Math. Model.*, vol. 37, no. 4, pp. 2430–2444, 2013.

[37] H. Doukas, "Modelling of linguistic variables in multicriteria energy policy support," *Eur. J. Oper. Res.*, vol. 227, no. 2, pp. 227–238, 2013.

[38] C. Yang, Q. Zhang, and S. Ding, "An evaluation method for innovation capability based on uncertain linguistic variables," *Appl. Math. Comput.*, vol. 256, pp. 160–174, Feb. 2015.

[39] R. M. Nefdt, "Linguistic modelling and the scientific enterprise," *Lang. Sci.*, vol. 54, pp. 43–57, Jan. 2016.

[40] H. Wang and Z. Xu, "Interactive algorithms for improving incomplete linguistic preference relations based on consistency measures," *Appl. Soft Comput.*, vol. 42, pp. 66–79, Oct. 2016.

[41] Y. He, H. Guo, M. Jin, and P. Ren, "A linguistic entropy weight method and its application in linguistic multi-attribute group decision making," *Nonlinear Dyn.*, vol. 84, pp. 399–404, Apr. 2016.

[42] T. C. Wang and Y. H. Chen, "Applying fuzzy linguistic preference relations to the improvement of consistency of fuzzy AHP," *Inf. Sci.*, vol. 178, no. 19, pp. 3755–3765, 2008.

[43] E. Cables, M. S. Garca-Cascales, and M. T. Lamata, "The LTOPSIS: An alternative to TOPSIS decision-making approach for linguistic variables," *Expert Syst. Appl.*, vol. 39, no. 2, pp. 2119–2126, 2012.

[44] J. Mezei, R. Wikstrm, and C. Carlsson, "Aggregating linguistic expert knowledge in type-2 fuzzy ontologies," *Appl. Soft Comput.*, vol. 35, pp. 911–920, Oct. 2015.

[45] P. Liu and F. Jin, "Methods for aggregating intuitionistic uncertain linguistic variables and their application to group decision making," *Inf. Sci.*, vol. 205, pp. 58–71, Nov. 2012.

[46] L. Abdullah and L. Najib, "A new type-2 fuzzy set of linguistic variables for the fuzzy analytic hierarchy process," *Expert Syst. Appl.*, vol. 41, no. 7, pp. 3297–3305, Jun. 2014.

[47] Z. Ayag and R. G. Özdemir, "A fuzzy AHP approach to evaluating machine tool alternatives," *J. Intell. Manuf.*, vol. 17, pp. 179–190, Apr. 2006.

[48] S. W. Hsiao and H. P. Wang, "Applying the semantic transformation method to product form design," *Design Stud.*, vol. 19, pp. 309–330, Jul. 1998.

[49] C. H. Lo, Y. C. Ko, and S. W. Hsiao, "A study that applies aesthetic theory and genetic algorithms to product form optimization," *Adv. Eng. Informat.*, vol. 29, no. 3, pp. 662–679, 2015.

[50] C. Tang *et al.*, "Product form design using customer perception evaluation by a combined superellipse fitting and ANN approach," *Adv. Eng. Informat.*, vol. 27, no. 3, pp. 386–394, 2013.

[51] Y. Ding *et al.*, "Using event related potentials to identify a user's behavioural intention aroused by product form design" *Appl. Ergonom.*, vol. 55, pp. 117–123, Jul. 2016.

[52] J. A. Diego-Mas and J. Alcaide-Marzal, "Single users' affective responses models for product form design," *Int. J. Ind. Ergon.*, vol. 53, pp. 102–114, May 2016.

[53] T. S. Huang and C. C. Fang, "The role of data mining in the product design and development process," in *Proc. 6th Int. Comput.-Aided Ind. Design Concept Design*, 2005, pp. 198–203.

[54] L. A. Zadeh, "Fuzzy sets," *Inf. Control*, vol. 8, no. 3, pp. 338–353, 1965.

[55] H. J. Zimmermann, *Fuzzy Sets, Decision Making, and Expert Systems*. Boston, MA, USA: Kluwer, 1987.

[56] C. H. Wang and H. S. Wu, "A novel framework to evaluate programmable logic controllers: A fuzzy MCDM perspective," *J. Intell. Manuf.*, vol. 27, no. 2, pp. 315–324, 2016.

[57] S. Hossein, F. Zahra, and M. Setareh, "Identifying and evaluating enterprise architecture risks using FMEA and fuzzy VIKOR," *J. Intell. Manuf.*, vol. 27, no. 2, pp. 475–486, 2016.

[58] A. Azarnivand and A. Malekian, "Analysis of flood risk management strategies based on a group decision making process via interval-valued intuitionistic fuzzy numbers," *Water Resour. Manage.*, vol. 30, no. 6, pp. 1903–1921, 2016.

[59] S. Vinodh, T. S. SaiBalagi, and P. Adithya, "A hybrid MCDM approach for agile concept selection using fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS," *Int. J. Adv. Manuf. Technol.*, vol. 83, no. 6, pp. 1979–1987, 2016.

[60] R. R. Yager and D. P. Filev, "Including probabilistic uncertainty in fuzzy logic controller modeling using Dempster-Shafer theory," *IEEE Trans. Syst., Man Cybern.*, vol. 25, no. 8, pp. 1221–1230, Aug. 1995.

[61] F. Shi, J. Xu, and S. Sun, "Fuzzy case-based reasoning in product style acquisition incorporating valence-arousal based emotional cellular model," *J. Appl. Math.*, vol. 2012, Art. no. 385079, Apr. 2012.

[62] M. C. Lin, C. C. Wang, M. S. Chen, and C. A. Chang, "Using AHP and TOPSIS approaches in customer-driven product design process," *Comput. Ind.*, vol. 59, pp. 17–31, Mar. 2008.

[63] Z. Güngör, G. Serhadlioglu, and S. E. Kesen, "A fuzzy AHP approach to personnel selection problem," *Appl. Soft Computing*, vol. 9, no. 2, pp. 641–646, 2009.

[64] J. G. de Graan, "Extensions of multiple criteria analysis method of T. L. Saaty," Presented at the EURO, Jul. 1980, pp. 22–25.

[65] P. J. M. Laarhoven and W. Pedrycz, "A fuzzy extension of Saaty's priority theory," *Fuzzy Sets Syst.*, vol. 11, nos. 1–3, pp. 229–241, 1983.

[66] J. J. Buckley, "Fuzzy hierarchical analysis," *Sets Syst.*, vol. 17, no. 3, pp. 233–247, 1985.

[67] C. H. Chou, G. S. Liang, and H. C. Chang, "A fuzzy AHP approach based on the concept of possibility extent," *Quality Quant.*, vol. 47, pp. 1–14, Mar. 2013.

[68] M. D. Shieh and Y. E. Yeh, "Developing a design support system for the exterior form of running shoes using partial least squares and neural networks," *Comput. Ind. Eng.*, vol. 65, no. 4, pp. 704–718, 2013.

[69] S. Butdee, "Hybrid feature modeling for sport shoe sole design," *Comput. Ind. Eng.*, vol. 42, no. 2, pp. 271–279, 2002.

[70] Y. H. Lin, C. Y. Chen, and M. H. Cho, "Influence of shoe/floor conditions on lower leg circumference and subjective discomfort during prolonged standing," *Appl. Ergon.*, vol. 43, no. 5, pp. 965–970, 2012.

[71] C. Wang *et al.*, "the impact of high-heeled shoes on ankle complex during walking in young women *in vivo* kinematic study based on 3D to 2D registration technique," *J. Electromyogr. Kinesiol.*, vol. 28, no. 7, p. 16, 2016.

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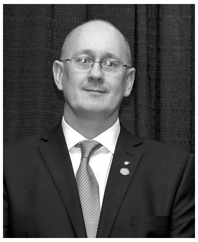

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