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Consumer-oriented product form design based on fuzzy logic: A case study of mobile phones

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Abstract

This paper presents a new fuzzy logic approach to determining the best combination of mobile phone form elements for matching a given product image. A consumer-oriented experimental study is conducted to examine the relationship between the key form elements and the product images of mobile phones. The most influential form elements of mobile phones are identified using the grey relational analysis. A new experimental process is conducted to objectively generate a set of fuzzy rules with the most influential form elements, based on the subjects' assessments of the simple–complex image on 33 representative mobile phone samples. The fuzzy rules generated outperform neural network models in predicting the product images of a mobile phone with a given set of form elements. The approach provides useful insights in facilitating and simulating the form design process of mobile phones.

Relevance to industry

Whether the consumers choose a product depends largely on their perception of the product images. The approach presented in the paper helps the product designers focus on the product forms that contribute most to the desirable product images. Although the mobile phone form design is used as a case study, the approach is applicable to other products with various design elements. The approach provides an effective mechanism for facilitating the consumer oriented product design process.

Keywords: Consumer-oriented product design; Fuzzy logic; Product form; Product image; Mobile phones; Kansei Engineering

1. Introduction

In a high competitive market such as mobile phones, the product designers need to provide the consumers with various styles of products. The product image plays an important role in the consumers' preference and choice of the product (Chuang et al., 2001). Based on the relationship between the product form and the product image perceived by the consumers, design support models have been developed to facilitate the product form design process (Hsiao and Tsai, 2005; Jindo et al., 1995). In particular, consumer-oriented Kansei Engineering has been developed as a methodology for transforming a consumer's feeling or image about a product into the design elements of the product (Nagamachi, 1995). It has been applied successfully in the product design field in order to explore the relationship between the feeling (perception of the product image) of the consumers and the design elements of the product. For example, Yang et al. (1999) developed a rule-based inference model with five rules and two inference approaches to translate a human feeling of a product into the design elements of the product. Lin et al. (2001) use the Kansei methodology to optimize the combination of the product forms and the product colors

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for mobile phones. Hsiao and Liu (2002) use a shape morphing and image prediction method to construct a three-dimensional (3-D) model in order to help the product designers quickly obtain the product form of a computer monitor.

Fuzzy logic has been developed to examine the relationship between variables in an observable system where the information available is subjective and imprecise (Negnevitsky, 2002). Fuzzy logic has been used in a wide range of fields, and some recent application results have highlighted its effective handling of imprecise known information for exploring unknown information (Baron et al., 2001; Chang and Yeh, 2004; Yeh et al., 2000). In particular, it provides an effective framework for modeling humans' feeling of words for decision making (Youji and Tomio, 1995). As such, fuzzy logic is well suited to model the product design process for describing the relationship between the product form (as the input variable) and the consumer's perception of the product image (as the output variable), where the consumer's perception is often expressed subjectively and imprecisely. For example, Park and Han (2004) build fuzzy rule-based models to associate the office chair design's variables with affective user satisfaction. Their study demonstrates that fuzzy rule-based models have a better prediction performance than conventional regression models. Hsiao and Tsai (2005) develop an automatic design system using fuzzy neural networks and genetic algorithms to help the product designers create a specific product form. In their study, a fuzzy neural network algorithm is applied to establish the relationships between the input form parameters and a series of product images. A genetic algorithm is then used to search for a near-optimal design that satisfies a specific product image.

In this paper, we present a new fuzzy logic approach to examining the relationship between the form elements of mobile phones and a specific product image of mobile phones. The development of this approach is motivated by the need to deal with the case study of mobile phones, which are currently the most popular consumer product and exhibit a wide variety of product forms. In modeling the complex form elements of mobile phones, it would be difficult to use the traditional method of asking the experts to generate and assess the fuzzy rules directly and subjectively, as used in the previous studies. As such, the new approach to be presented constructs the fuzzy rules in an objective manner based on a new consumer-oriented experimental process. This approach is particularly suitable for modeling a system or a product with multiple input variables (e.g. multiple product form elements) and multiple output variables (e.g. multiple product images), as evidenced by the case study of mobile phones conducted in this paper.

In subsequent sections, we first describe a consumer oriented experimental process for extracting the representative samples and form elements of mobile phones, which are used as numerical data sets for building and testing the fuzzy logic model. We then present the new fuzzy logic approach to construct a set of fuzzy rules for matching the extracted form elements with a specific product image. Finally, we compare the performance of the fuzzy logic model with existing models in terms of their prediction ability.

2. Consumer-oriented experiments

Consumer-oriented Kansei Engineering has been used to link the consumer's feeling of a product, represented by an image word pair, with the design elements of the product, using surveys or experiments (Nagamachi, 1995). In this paper, we conduct an experimental study based on the process of consumer-oriented Kansei Engineering in order to collect numerical data about the relationship between an image word pair and the form elements of mobile phones. In what follows, we present the experimental study and its results in the context of the four primary phases of consumer-oriented Kansei Engineering.

2.1. Experimental subjects

The experimental study involved 35 subjects, divided into three groups. Except for the second group, we investigated the views of young people as they usually pay more attention to mobile phones than other age groups. We asked the first group, consisting of eight males and seven females, to extract the representative samples of mobile phones. The average age of the group members was 22.8 and each subject had more than 5 years' experience of using mobile phones. We asked the second group, formed by five expert mobile phone designers (two males and three females), to perform the morphological analysis in order to extract the form elements of mobile phones. The five experts in this group had at least 6 years of product design experience. The third group had eight males and seven females for evaluating the product image of the experimental samples, whose result is to be used as a basis for evaluating the performance of the fuzzy logic model. The average age of the 15 subjects in the third group was 25.3 and each had more than 5 years' experience of using mobile phones.

2.2. Experimental samples

In this paper, we considered only mobile phones with no flip cover for the experimental samples, as shown in Fig. 1. To identify the commonly used form elements of mobile phones in the market, we first selected 100 mobile phones of various makers and models, which entered the market during 1999–2001. We then asked the 15 subjects of the first group to classify these 100 mobile phones based on their similarity degree, using the Kawakida Jirou method (Cross, 1994). This method was introduced by Kawakida Jirou in 1953 for classifying ideas, concepts, or objects into several groups by their similarity degree. Finally, we

Fig. 1. The 33 representative mobile phone samples.

performed the multidimensional scaling (MDS) analysis and the cluster analysis (Hair et al., 1995) based on the separation result obtained from the 15 subjects. This result was then used to extract the 33 representative mobile phone samples (as shown in Fig. 1) for identifying the common form elements and for subsequently building and testing the fuzzy logic model. The experimental procedure for extracting the mobile phone samples is summarized by the following nine steps (Lai et al., 2005, 2006; Lin et al., 2001):

Step 1: Select 100 mobile phones of various makers and models.
Step 2: Make 100 small paper cards according to the original size of each mobile phone.
Step 3: Separate the small paper cards into several groups by their similarity degree, using the Kawakida Jirou method.
Step 4: Build a similarity matrix from the separation result obtained at Step 3.
Step 5: Transform the similarity matrix into a dissimilarity matrix for the analysis at Step 6.
Step 6: Apply the MDS analysis to the dissimilarity matrix data.
Step 7: Choose several dimensions as a result of the MDS analysis with stress and squared correlation variables.
Step 8: Perform the cluster analysis based on the MDS result, and then generate a cluster tree diagram.
Step 9: Extract the representative mobile phone samples based on the cluster tree diagram.

2.3. Morphological analysis of product form elements

A two-step morphological analysis was used to extract the form elements of the 33 representative mobile phone samples given in Fig. 1. In the first step, the five subjects (expert product designers) of the second group were asked to write down the key form elements of the mobile phones individually, according to their knowledge and experience. The survey results were grouped into two parts: form feature and form treatment. The form feature part included the size and shape of outline components making up the mobile phone, such as buttons, icons, the screen, or the body shell. The form treatment part indicated the relationship between the outline components, e.g., the equidistance arrangement of the buttons or the size rate of the screen and the body shell. In the second step, the five subjects formed a focus group (Nielsen, 1993) to combine similar opinions of the survey results.

As a result of the morphological analysis, Table 1 shows the nine form elements extracted from the 33 representative mobile phone samples, together with their associated form types. Each form element has different form types of its own, ranging from 2 to 4, as indicated by the type number 1, 2, 3 or 4 in Table 1. For example, the "bottom shape (X_3)" element has three form types, including "line (L, X_{31})", "curve (C, X_{32})", and "arc (A, X_{33})".

Table 1
Morphological analysis on the 33 representative mobile phone samples

	Elements	Type 1	Type 2	Type 3	Type 4
1.	Top Shape (X_1)	Line (L, X_{11})	Curve (C, X_{12})	Arc (A, X_{13})	Irregular (I, X_{14})
2.	Body Shape (X_2)	Concave Curve (CC, X_{21})	Parallel Line (PL, X_{22})	Raised Curve (RC, X_{23})	
3.	Bottom Shape (X_3)	Line (L, X_{31})	Curve (C, X_{32})	Arc (A, X_{33})	
4.	Length and Width Ratio of Body (X_4)	Wide Ratio 2:1 (WR, X_{41})	Middle Ratio 2.5:1 (MR, X_{42})	Slender Ratio 3:1 (SR, X_{43})	
5.	Function Buttons Style (X_5)	Other Style (OS, X_{51})	Symmetry Style (SS, X_{52})	With Large Button (LB, X_{53})	
6.	Number Buttons Arrangement (X_6)	Regular (R, X_{61})	Irregular (I, X_{62})		
7.	Screen Size (X_7)	TV Ratio 4:3 (TR, X_{71})	Movie Ratio 16:9 (MR, X_{72})	Other Ratio (OR, X_{73})	
8.	Screen Mask and Function Buttons (X_8)	Independence (ID, X_{81})	Interdependence (IT, X_{82})	Function Buttons Dependence on Screen Mask (D, X_{83})	
9.	Outline Division Style (X_9)	Normal Division (ND, X_{91})	Special Division (SD, X_{92})	Rim Division (RD, X_{93})	

2.4. Consumer's perception of the product images

The 15 subjects of the third group were involved in evaluating the degree to which the 33 representative mobile phone samples match a given product image. Pairs of image words are often used to describe the consumer's psychological feeling and perception about the image of a new product. To extract the representative image word pairs for describing the consumer's perception of the product image about mobile phones, we carried out the following steps (Lin et al., 2001):

Step 1: Collect a large set of image word pairs from magazines and product catalogs.

Step 2: Evaluate the collected image word pairs using the semantic differentials (SD) method (Osgood and Suci, 1957).

Step 3: Apply the factor analysis and cluster analysis to the result of SD obtained at Step 2.

Step 4: Determine the representative image word pairs of the product images based on the analyses performed at Step 3.

We finally selected three representative image word pairs for describing the product images of mobile phones, including simple–complex (S–C), handsome–rustic (H–R) and leisure–formal (L–F). We then used these three word pairs to evaluate the consumer's perception of the 33 representative mobile phone samples, using the quantitative theory type I (Nagamachi, 1989) and neural networks (Nelson and Illingworth, 1991) methods. The results of both methods showed that the S–C word pair (the coefficient of determination (R^2) being 0.80 and the prediction rate (PR) being 91.67%) had the highest prediction consistency, as compared to the H–R (R^2 being 0.69 and PR being 75.00%) and L–F (R^2 being 0.76 and PR being 50.00%) word pairs. As such, we used the S–C word pair as the primary product image of mobile phones in order to construct the fuzzy logic model as an illustration for the fuzzy logic approach developed in this paper. Two other product images were used for further performance evaluation of the fuzzy logic model.

We used a seven-point scale (1–7) of the SD method to obtain the assessment value for the S-–C image of a given mobile phone. We asked the 15 subjects of the third group to assess the product form (look) of the 33 representative mobile phone samples on a simplicity–complexity scale of 1–7, where 1 and 7 represented the simplest look and the most complex look, respectively. Table 2 shows the assessment result. For each mobile phone in Table 2, the first column indicates the mobile phone number and Columns 2–10 show the corresponding type number for its nine form elements, respectively, as given in Table 1. For example, mobile phone no. 18 has the "simplest" product image with an average S–C value of 2.533 as compared to other mobile phones, and its corresponding

Table 2
Numerical data source for the 33 representative mobile phone samples

Phone no.	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	S–C value				H–R value	Y–R value
										Average	Min	Max	Standard deviation	Average	Average
1	2	3	1	3	2	2	1	3	1	4.47	2	7	1.50	5.03	4.87
2	2	1	1	2	1	2	1	3	2	3.13	1	7	1.75	3.37	3.32
3	1	1	2	1	2	1	2	2	1	2.87	1	6	1.71	5.86	5.24
4	3	1	1	2	2	1	3	1	1	5.53	3	7	1.31	5.76	4.62
5	4	2	1	2	1	2	3	1	3	5.53	3	7	1.31	4.87	3.94
6	1	3	1	2	2	1	1	2	1	6.40	5	7	0.71	3.63	5.08
7	2	3	1	2	2	1	2	3	2	6.87	5	7	0.50	2.90	3.58
8	4	2	2	3	2	2	1	3	2	6.80	5	7	0.54	3.27	4.82
9	2	3	1	1	3	1	2	1	3	4.60	2	7	1.78	4.67	4.41
10	2	1	1	2	2	1	1	1	1	6.20	4	7	1.11	6.74	6.64
11	3	3	3	3	2	2	1	1	3	6.60	4	7	0.88	2.54	2.07
12	2	2	1	2	2	1	2	2	1	4.53	2	7	1.86	6.69	6.74
13	1	3	1	2	3	1	3	2	1	3.93	1	6	1.44	5.65	5.86
14	3	3	2	3	3	1	2	2	2	6.93	6	7	0.25	5.65	5.81
15	2	3	1	3	3	1	1	2	1	5.60	2	7	1.99	5.24	4.82
16	1	2	1	3	3	1	1	1	1	2.73	1	7	1.65	3.68	2.28
17	1	2	1	2	1	1	2	3	2	4.33	1	7	2.02	5.08	5.03
18	2	3	1	2	3	1	2	2	2	2.53	1	5	1.36	4.20	3.06
19	2	1	2	2	3	1	2	1	3	4.53	2	7	1.82	3.16	1.82
20	2	3	2	2	3	1	1	3	1	3.20	1	7	1.72	1.87	2.18
21	2	3	2	2	2	1	1	3	1	5.53	4	7	1.15	2.96	3.84
22	2	3	2	2	1	1	1	1	1	6.87	6	7	0.34	3.63	3.42
23	2	3	1	2	2	2	1	3	2	4.47	2	7	1.59	2.96	3.99
24	2	3	1	2	2	1	2	3	1	3.67	1	6	1.45	4.30	3.58
25	3	1	1	2	3	1	2	3	2	3.07	1	7	2.02	2.96	1.76
26	3	1	3	3	2	1	2	2	1	4.53	1	7	1.59	4.20	2.07
27	3	3	1	3	2	2	1	3	1	3.60	1	7	1.82	3.89	3.58
28	1	3	2	2	3	2	1	3	2	4.60	2	7	1.99	1.09	1.71
29	2	3	2	3	3	1	1	1	1	4.93	2	7	1.73	2.18	1.76
30	1	1	1	3	3	1	1	1	1	5.33	3	7	1.54	1.71	2.44
31	2	1	3	1	3	1	1	2	2	3.73	1	7	2.11	3.53	1.56
32	2	1	3	2	3	2	2	2	3	3.53	1	7	1.75	4.51	3.22
33	2	2	3	2	2	1	2	3	3	3.73	1	7	1.84	3.42	2.44

type numbers of the nine form elements are $X_1 = 2$, $X_2 = 3$, $X_3 = 1$, … , and $X_9 = 2$, respectively. Table 2 provides the numerical data source for constructing the fuzzy rules to determine the value of the S–C image for a given mobile phone.

3. The fuzzy logic model

In this section, we explain how the fuzzy logic model with fuzzy rules can be constructed to determine the value of the S–C image for a given mobile phone. Building a fuzzy logic model involves the definition of the input and output linguistic variables and the construction of the fuzzy rules.

3.1. Defining the input and output linguistic variables

To find out the influential factors of a product for describing a given product image, the grey relational analysis (GRA) (Deng, 1982) can be used (Lai et al., 2005). We performed the GRA to determine the most influential form elements of mobile phones for the S–C image. With the value ranging from 0 to 1, the grey relational degree $r(X_0, X_i)$ between the S–C image (X_o) and each of the nine form element (X_i, $i = 1, 2, \ldots, 9$) is obtained by the GRA as follows:

$$r(X_0, X_1) = 0.811,\ r(X_0, X_2) = 0.755,\ r(X_0, X_3) = 0.714,$$
$$r(X_0, X_4) = 0.794,\ r(X_0, X_5) = 0.795,\ r(X_0, X_6) = 0.751,$$
$$r(X_0, X_7) = 0.681,\ r(X_0, X_8) = 0.758,\ \text{and}\ r(X_0, X_9) = 0.659.$$

If $r(X_0, X_i) > r(X_0, X_j)$, then the form element X_i is closer to the S–C image X_0 than the form element X_j. The higher the $r(X_0, X_i)$ value, the more influential the form element X_i. As such, the "top shape" element (X_1), with the highest GRA value of 0.811, affects the S–C image the most, followed by the "function buttons style" element (X_5) and the "length and width ratio of body" element (X_4). This implies that the designers should focus their attention more on these three most influential form elements, when the objective of designing a mobile phone is to achieve a desirable S–C image. On the contrary, the designers may pay less attention to the less influential form elements such as "outline division style" (X_9), the "screen size" element (X_7) and the "bottom shape" element (X_3), as these elements have a relatively small contribution to the consumers' perception of the S–C image.

As suggested in our previous study (Lai et al., 2005), the result of the GRA can help the product designers focus on the most influential form elements in the design process for achieving a desirable product image. This result can be used to simplify the modeling process, and the performance of the model constructed will not be compromised by using only the most influential form elements. In line with the outcome of our previous study, we construct the fuzzy rules of the fuzzy logic model by using the six most influential form elements of mobile phones for the S–C image. As such, six input linguistic variables are used in the fuzzy rules, including top shape (X_1, GRA = 0.811), body shape (X_2, GRA = 0.755), length and width ratio of body (X_4, GRA = 0.794), function buttons style (X_5, GRA = 0.795), number buttons arrangement (X_6, GRA = 0.751), and screen mask and function buttons (X_8, GRA = 0.758). The output linguistic variable (Y) is the S–C image, whose value is the average S–C value assessed by the 15 subjects of the third group, as shown in Table 2.

3.2. Determining the membership functions of linguistic variables

Fuzzy numbers can have a variety of shapes. A triangular or a trapezoid form often provides an adequate representation of the expert knowledge, and significantly simplifies the computational process (Yeh and Deng, 2004). In practical applications, the triangular or trapezoid form of the membership function is used most often for representing fuzzy numbers (Klir and Yuan, 1995). Eq. (1) shows the membership function $\mu_A(x)$ of a triangular fuzzy number represented by a triple (a, b, c), where a, b, and c are real numbers with $a \leqq b \leqq c$:

$$\mu_A(x) = \begin{cases} 0, & x < a, \\ \dfrac{x-a}{b-a}, & a \leqslant x \leqslant b, \\ \dfrac{x-c}{b-c}, & b \leqslant x \leqslant c, \\ 0, & x > c. \end{cases} \tag{1}$$

The triangular fuzzy number (a, b, c) can be used to give the approximate value range of a linguistic term. b is the most possible value of the term, and a and c are the lower and upper bounds, respectively, used to reflect the fuzziness of the term. In this paper, we use the triangular or trapezoid membership functions to represent the values of various form types (i.e. the linguistic terms) of the six form elements (as the six input linguistic variables) used in the fuzzy rules of the fuzzy logic model, as shown in Fig. 2.

Each linguistic variable in Fig. 2 is defined according to the number of the form types of its underlying form element, given in Table 1. For example, "top shape (X_1)" has four form types (line, curve, arc, and irregular); therefore, four linguistic terms (line, curve, arc, and irregular) characterized by four triangular fuzzy numbers are used, as shown in Table 3 and Fig. 2(a). The scale value of 1–3 is given for a specific top shape to indicate the degree to which it matches the first three top shape types as characterized by the corresponding terms (line, curve, and arc), respectively. For example, a value of 2.5 indicates the actual top shape is a combination of 50% Type 2 (curve) and 50% Type 3 (arc) of the "top shape" element defined in Table 1. We use a single value of 4 for the "irregular" shape to indicate that this shape type has no relevance to or association with the first three types. As another example, "number buttons arrangement (X_6)" has two form types (regular and irregular); therefore, two linguistic terms

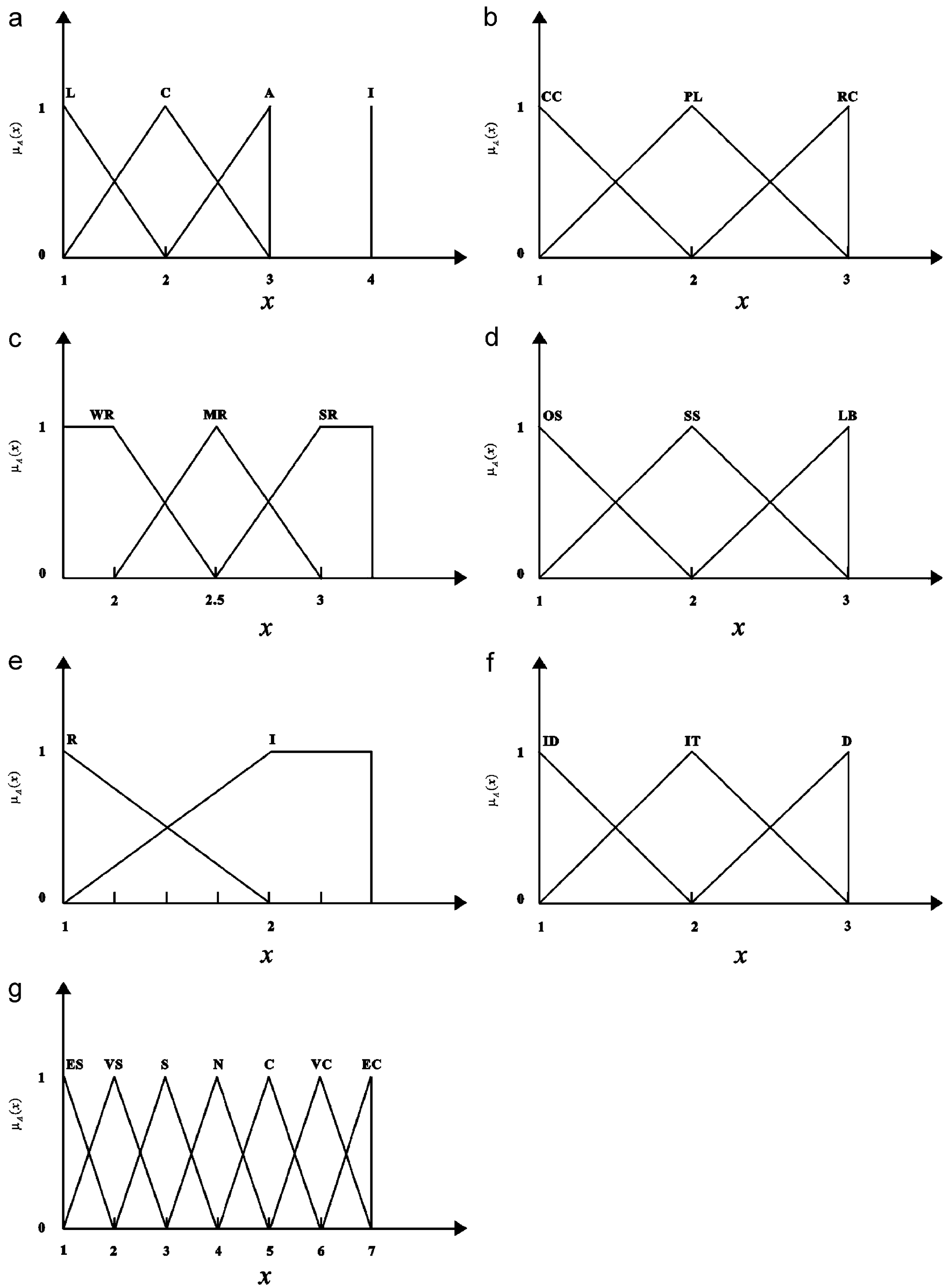


Fig. 2. Membership functions of the linguistic terms for the linguistic variables used in the fuzzy logic model: (a) top shape (X_1), (b) body shape (X_2), (c) length and width ratio of body (X_4), (d) function buttons style (X_5), (e) number buttons arrangement (X_6), (f) screen mask and function buttons (X_8), (g) S–C value (Y).

(regular and irregular) characterized, respectively, by a triangular fuzzy number and a trapezoid fuzzy number are used, as shown in Fig. 2(e). For a "number button arrangement" more irregular than X_{62}, a value of greater than 2 with a membership degree of 1.0 is used.

As discussed in Section 2.4, the 15 subjects used a seven-point scale of the SD method to assess the degree to which the look of each of the 33 representative mobile phone samples matches the S–C image. As a result, we obtain the S–C value ranging from 1 to 7 as listed in Table 2.

The seven possible S–C values are fuzzified with seven triangular fuzzy numbers to represent the seven value states (i.e. the seven linguistic terms) of the S–C image (as the output linguistic variable), respectively, shown as in Table 4 and Fig. 2(g).

3.3. Constructing the fuzzy rules

As a means of expressing the experts' domain knowledge, fuzzy rules constructed may vary among the experts and even for the same expert at different times. To obtain the fuzzy rules in an objective manner, the 15 subjects individually assessed the product form (look) of the 33 representative mobile phone samples on an S–C scale of 1–7, as discussed in Section 2.4. The average value of the subjects' assessments is used as the output of the fuzzy rules, and usually has a partial membership in the corresponding linguistic terms as shown in Fig. 3. For example, the average S–C value of the subjects' assessment for phone no. 2 is 3.13, as given in Table 2. As Fig. 3 shows, the S–C value of 3.13 is a member of the 'S' (simple) linguistic term with a membership degree of 0.87 $(= (1-0) \times (4-3.13)/(4-3)+0)$; and it is also a member of the 'N' (neutral) linguistic term with a membership degree of 0.13 $(= (1-0) \times (3.13-3)/(4-3)+0)$. The membership degree represents the degree of support (DoS) for the corresponding rule. With a value range between 0 and 1, the DoS indicates the rule's weight (Negnevitsky, 2002). The last column of Table 5 shows the DoS of the fuzzy rules.

To reflect the product form design process involving multiple form elements, we use the fuzzy rules with multiple conditions (antecedents), as follows:

$$\text{Rule}: \text{IF } X_1 \text{ is } A_1 \text{ AND } X_2 \text{ is } A_2 \ldots \text{AND } X_n \text{ is } A_n \quad \text{THEN } Y \text{ is } B, \tag{2}$$

where A_1, A_2, …, A_n and B are the fuzzy linguistic terms, taken by the input linguistic variables X_1, X_2, …, X_n and the output linguistic variable Y, respectively. These terms are represented by a triangular or trapezoid fuzzy number. With the experimental study on the 33 representative mobile phone samples, a set of 66 $(33 \times 2 = 66)$ fuzzy rules is constructed. Each fuzzy rule associates a given combination of mobile phone form elements with a value state of the S–C image. Table 5 shows these fuzzy rules. For example, Rule 1 states that "If the top shape (X_1) is curve (C), the body shape (X_2) is raised curve (RC), the length and width ratio of body (X_4) is slender ratio (SR), function buttons style (X_5) is symmetry style (SS), number buttons arrangement (X_6) is irregular (I), and screen mask and function buttons (X_8) is dependence (D), then the S–C value is neutral (N) with a degree of support (DoS) of 0.53".

Table 3
Triangular fuzzy numbers for the 'top shape (X_1)' form element

Linguistic term	Line (L)	Curve (ML)	Arc (MH)	Irregular (H)
Membership function	(1, 1, 2)	(1, 2, 3)	(2, 3, 3)	(4, 4, 4)

Table 4
Triangular fuzzy numbers for the value states of the S–C image

Linguistic term	Extremely simple (ES)	Very simple (VS)	Simple (S)	Neutral (N)	Complex (C)	Very complex (VC)	Extremely complex (EC)
Membership function	(1, 1, 2)	(1, 2, 3)	(2, 3, 4)	(3, 4, 5)	(4, 5, 6)	(5, 6, 7)	(6, 7, 7)

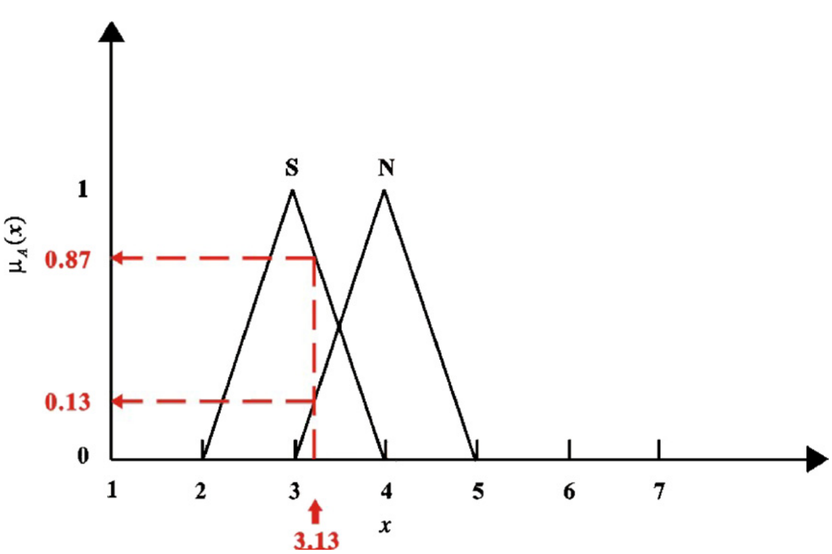


Fig. 3. Membership degrees of an S–C value in the output linguistic terms.

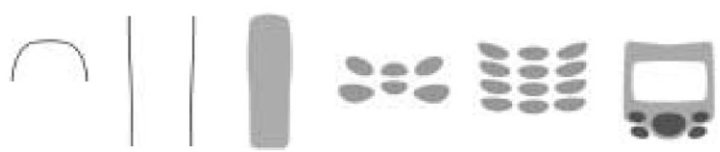
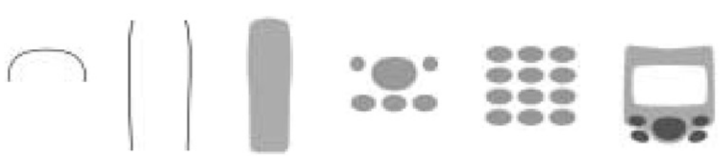
Table 5
Fuzzy rules for determining the S–C value of mobile phone form elements

Rule	IF (Antecedent)						THEN (Consequent)	
	X_1	X_2	X_4	X_5	X_6	X_8	S–C (Y)	DoS
1	C	RC	SR	SS	I	D	N	0.53
2	C	RC	SR	SS	I	D	C	0.47
3	C	CC	MR	OS	I	D	S	0.87
4	C	CC	MR	OS	I	D	N	0.13
5	L	CC	WR	SS	R	IT	S	0.87
6	L	CC	WR	SS	R	IT	VS	0.13
7	A	CC	MR	SS	R	ID	VC	0.53
8	A	CC	MR	SS	R	ID	EC	0.47
9	I	PL	MR	OS	I	ID	VC	0.53
10	I	PL	MR	OS	I	ID	C	0.47
11	L	RC	MR	SS	R	IT	VC	0.60
12	L	RC	MR	SS	R	IT	EC	0.40
13	C	RC	MR	SS	R	D	EC	0.87
14	C	RC	MR	SS	R	D	VC	0.13
15	I	PL	SR	SS	I	D	VC	0.80
16	I	PL	SR	SS	I	D	C	0.20
17	C	RC	WR	LB	R	ID	C	0.60
18	C	RC	WR	LB	R	ID	N	0.40
19	C	CC	MR	SS	R	ID	VC	0.80
20	C	CC	MR	SS	R	ID	EC	0.20
21	A	RC	SR	SS	I	ID	EC	0.60
22	A	RC	SR	SS	I	ID	VC	0.40
23	C	PL	MR	SS	R	IT	C	0.53
24	C	PL	MR	SS	R	IT	N	0.47
25	L	RC	MR	LB	R	IT	N	0.93
26	L	RC	MR	LB	R	IT	S	0.07
27	A	RC	SR	LB	R	IT	EC	0.93
28	A	RC	SR	LB	R	IT	VC	0.07
29	C	RC	SR	LB	R	IT	VC	0.60
30	C	RC	SR	LB	R	IT	C	0.40
31	L	PL	SR	LB	R	ID	S	0.73
32	L	PL	SR	LB	R	ID	VX	0.27
33	L	PL	MR	OS	R	D	N	0.67
34	L	PL	MR	OS	R	D	C	0.33
35	C	RC	MR	LB	R	IT	S	0.53
36	C	RC	MR	LB	R	IT	VS	0.47
37	C	CC	MR	LB	R	ID	C	0.53
38	C	CC	MR	LB	R	ID	N	0.47
39	C	RC	MR	LB	R	D	S	0.80
40	C	RC	MR	LB	R	D	N	0.20
41	C	RC	MR	SS	R	D	VC	0.53
42	C	RC	MR	SS	R	D	C	0.47
43	C	RC	MR	OS	R	ID	EC	0.87
44	C	RC	MR	OS	R	ID	VC	0.13
45	C	RC	MR	SS	I	D	N	0.53
46	C	RC	MR	SS	I	D	C	0.47
47	C	RC	MR	SS	R	D	N	0.67
48	C	RC	MR	SS	R	D	S	0.33
49	A	CC	MR	LB	R	D	S	0.93
50	A	CC	MR	LB	R	D	N	0.07
51	A	CC	SR	SS	R	IT	C	0.53
52	A	CC	SR	SS	R	IT	N	0.47
53	A	RC	SR	SS	I	D	N	0.60
54	A	RC	SR	SS	I	D	S	0.40
55	L	RC	MR	LB	I	D	C	0.60
56	L	RC	MR	LB	I	D	N	0.40
57	C	RC	SR	LB	R	ID	C	0.93
58	C	RC	SR	LB	R	ID	N	0.07
59	L	CC	SR	LB	R	ID	C	0.67
60	L	CC	SR	LB	R	ID	VC	0.33
61	C	CC	WR	LB	R	IT	N	0.73

Table 5 (*continued*)

Rule	IF (Antecedent)						THEN (Consequent)	
	X_1	X_2	X_4	X_5	X_6	X_8	S–C (Y)	DoS
62	C	CC	WR	LB	R	IT	S	0.27
63	C	CC	MR	LB	I	IT	N	0.53
64	C	CC	MR	LB	I	IT	S	0.47
65	C	PL	MR	SS	R	D	N	0.73
66	C	PL	MR	SS	R	D	S	0.27

Table 6
Input and output values of the five testing samples

Sample		X_1	X_2	X_4	X_5	X_6	X_8	Y (S-C value)
1		(L, X_{11})	(CC, X_{21})	(SR, X_{43})	(LB, X_{53})	(R, X_{61})	(ID, X_{81})	5.32
2		(C, X_{12})	(CC, X_{21})	(SR, X_{43})	(SS, X_{52})	(I, X_{62})	(IT, X_{82})	4.00
3		(C, X_{12})	(RC, X_{23})	(MR, X_{42})	(SS, X_{52})	(I, X_{62})	(D, X_{83})	4.48
4		(A, X_{13})	(RC, X_{23})	(SR, X_{43})	(LB, X_{53})	(R, X_{61})	(IT, X_{82})	6.88
5		(L, X_{11})	(PL, X_{22})	(MR, X_{42})	(LB, X_{53})	(I, X_{62})	(D, X_{83})	3.76

In the inference process, all fuzzy rules are effectively executed in parallel (Chang et al., 1998). The given input determines the degree of truth (or match) for the corresponding antecedents in each fuzzy rule. This limits the degree of truth for the consequent in the rule to no more than the same degree for any of its antecedents. The conclusion (the output) of each rule is thus obtained by truncating the fuzzy number for the consequent in the rule by the minimum degree of truth for its antecedents. Taking the union (or the maximum operation) of all the truncated fuzzy numbers for all effective fuzzy rules constitutes the overall inference conclusion, which is also a fuzzy number. This aggregated fuzzy number thus reflects the degree of contribution from each antecedent in the given set of fuzzy rules. To translate the aggregated fuzzy number obtained by the inference process into an executable action, a defuzzification method is required. The defuzzification of a fuzzy number will result in a single-scalar value. For this study, we use the most commonly used center-of-maximum (COM) method (Zimmermann, 1996), computed as

$$^{y}\mathrm{COM} = \frac{\sum_i [\mu(y_i) \times y_i]}{\sum_i \mu(y_i)}, \tag{3}$$

where i represents each linguistic term of a linguistic output variable (e.g. the S–C image); y_i is the maximum of each linguistic term i (e.g. simple or neutral), and $\mu(y_i)$ is the aggregated output membership function.

3.4. Testing the fuzzy rules

To verify the fuzzy rules constructed in determining the S–C value for a given design combination of mobile phone form elements, we use the five testing samples shown in Table 6. Columns 2–7 of Table 6 show the corresponding types for each of the six influential form elements. The last column of Table 6 shows the corresponding output S–C value, defuzzified by the COM defuzzification method. With the use of a seven-point scale, the output value ranges from 1 to 7.

Table 7
Neurons of the NN and GRA-NN models

The NN model	
Input layer	27 neurons for 27 types of the 9 form elements.
Hidden layer	14 neurons, $(27+1)/2 = 14$.
Output layer	01 neuron for the S–C value.
The GRA-NN model	
Input layer	18 neurons for 18 types of the 6 form elements.
Hidden layer	10 neurons, $(18+1)/2 = 9.5 = 10$.
Output layer	01 neuron for the S–C value.

4. Performance evaluation and discussion

To examine the prediction ability of the fuzzy logic model, we compare its performance with the neural network (NN) and GRA-NN models developed in our previous study (Lai et al., 2005). These NN-based models outperform other models for determining the best combination of mobile phone form elements for achieving a given product image. The NN model uses all the nine form elements identified from the experimental study, while the GRA-NN model uses the six most influential elements, as used in the fuzzy logic model. Therefore, the NN model has 27 input neurons, which are the 27 types of the niine form elements given in Table 1. The GRA-NN model has 18 input neurons, which are the 18 types of the six most influential form elements. Table 7 shows the neurons of the NN model and the GRA-NN model, including the input layer, the hidden layer, and the output layer. For both models, if a mobile phone has a particular form element type, the value of the corresponding input neuron is 1; otherwise, the value is 0. The output neuron of both models is the S–C value, ranging from 1 and 7.

To evaluate the performance of a model, the root of mean square errors (RMSE) is commonly used, given as

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - x_0)^2}{n}}, \tag{4}$$

where x_i is the ith output value predicted by the model and x_0 is the expected values assessed by the subjects in the

Table 8
The RMSE results of the fuzzy logic, NN and GRA-NN models

S–C value	Testing sample					RMSE
	1	2	3	4	5	
Assessed by the subjects	5.80	3.80	5.80	5.87	4.60	
The fuzzy logic model	5.32	4.00	4.48	6.88	3.76	0.8645 (12.35%)
The NN model	5.24	3.76	1.59	3.07	2.40	2.4787 (35.41%)
The GRA-NN model	5.33	4.53	2.94	5.25	2.30	1.7094 (24.42%)
H–R value						
Assessed by the subjects	5.08	6.05	6.24	4.10	1.39	
The fuzzy logic model	4.67	5.23	4.79	4.95	2.58	1.0080 (14.40%)
The NN model	5.51	3.44	3.13	2.07	1.64	2.0419 (29.17%)
The GRA-NN model	3.02	4.78	2.35	2.70	1.99	2.1588 (30.84%)
Y–R value						
Assessed by the subjects	5.53	6.18	6.22	3.73	1.71	
The fuzzy logic model	6.22	4.06	4.48	4.83	2.76	1.4357 (20.51%)
The NN model	4.65	3.01	4.39	1.89	2.12	1.8830 (26.90%)
The GRA-NN model	4.13	4.17	3.81	2.68	2.21	1.6226 (23.18%)

experiment. If there is no difference or error between the output value and the expected value, the RMSE is 0.

The second row of Table 8 shows the average S–C value of the five testing samples assessed by the 15 subjects of the third group using the SD method with a seven-point scale. With the five testing samples as the input, Table 8 shows their corresponding S–C value predicted by using the fuzzy logic model, NN and GRA-NN models, respectively. The last column of Table 8 shows the RMSE of these models, in comparison with the S–C values assessed by the 15 subjects. The fuzzy logic model has the lowest RMSE (0.8645, 12.35% = 0.864/7), as compared to the NN model (the RMSE being 2.4787, 35.41% = 2.4787/7) and the GRA-NN model (the RMSE being 1.7094, 24.42% = 1.7094/7). The result indicates that the fuzzy logic model has the highest consistency (87.65% = 100−12.35%) for predicting the value of the S–C image, thus suggesting that it is a promising approach for matching a given set of product form elements with a specific product image.

To further examine the performance of the fuzzy logic model, we choose two other product images: handsome-rustic (H–R) and young–ripe (Y–R). Like the S–C image, we build two additional fuzzy logic models for the H–R and Y–R images, respectively. The 15 subjects of the third group were involved in the process again, using the SD method with a seven-point scale. Tables 2 and 8 show the assessment results for the 33 representative mobile phone samples and the five testing samples, respectively. The last two columns of Table 2 show the average H–R and Y–R values assessed by the subjects, respectively. Table 8 shows the average H–R and Y–R values assessed by the 15 subjects for the five testing samples, together with the values predicted by using the fuzzy logic, NN and GRA-NN models, respectively. In terms of the H–R and Y–R images, the result of Table 8 shows that the fuzzy logic model also has the lowest RMSE, as compared to the NN model and the GRA-NN model. This result is consistent with the outcome for the S–C image.

The performance of the fuzzy logic model suggests that it can be used to help the product designers work out the best combination of mobile phone form elements for a particular design concept represented by a product image word pair such as simple–complex, handsome–rustic, or young–ripe. The fuzzy logic approach thus provides an effective mechanism for designing a new mobile phone that reflects a desirable product image. For example, the product designers can use the fuzzy logic model to input the values of the form elements, and then obtain the predicted value for the targeted product image. If the product designers are not satisfied with the predicted value,

Table 9
Two sets of mobile phone form elements as the input to the fuzzy logic model

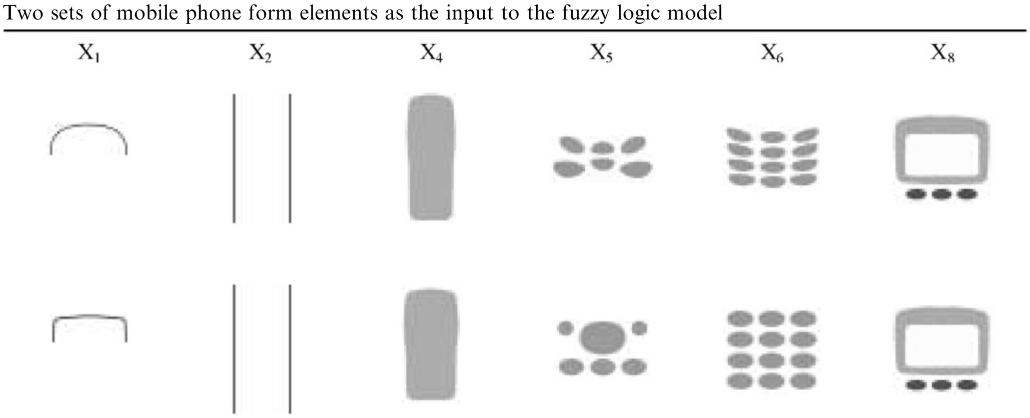


Fig. 4. A 3-D mobile phone model with the CAD system and the VR technology.

they can modify the combination of the form elements, and subsequently obtain a new value. This process can be performed efficiently until a satisfied value is obtained.

In product design settings where the consumers or designers need to consider more than one product image, the multiple conditions fuzzy if–then rules can be used. For example,

$$\begin{aligned}\text{Rule}: \ & \text{IF } X_1 \text{ is } A_1 \text{ AND } X_2 \text{ is } A_2 \ldots \text{AND } X_n \text{ is } A_n,\\ & \text{THEN } Y_1 \text{ is } B_1 \text{ AND } Y_2 \text{ is } B_2 \ldots \text{AND } Y_n \text{ is } B_n,\end{aligned} \tag{5}$$

where A_1, A_2, …, A_n and B_1, B_2, …, B_n are the fuzzy linguistic terms, taken by the input linguistic variables X_1, X_2, …, X_n and the output linguistic variables Y_1, Y_2, …, Y_n, respectively. The output linguistic variables Y_1, Y_2, …, Y_n represent a set of product image word pairs. For example, the product designers can individually input the values of the six mobile phone form elements as "$X_1 = 2$, $X_2 = 2$, $X_4 = 2$, $X_5 = 2$, $X_6 = 2$, $X_8 = 1$", or "$X_1 = 1$, $X_2 = 2$, $X_4 = 1$, $X_5 = 3$, $X_6 = 1$, $X_8 = 1$" to the fuzzy logic model, as shown in Table 9. Then the fuzzy logic model will output the values of the product images as "the S–C value is 2.46, H–R is 4.60, and Y–R is 2.69", or "the S–C value is 1.80, H–R is 3.92, and Y–R is 3.76".

In addition, the fuzzy logic model can be used, in conjunction with a computer aid design (CAD) system or virtual reality (VR) technology (Jindo et al., 1995), to build a 3-D model for facilitating and simulating the design process. As an illustration, Fig. 4 shows a 3-D model for the two mobile phones whose form elements are given in Table 9, respectively.

5. Conclusion

In this paper, we have presented a fuzzy logic approach for matching the key form elements of a product with a given product image as perceived by the consumers. To illustrate the approach, we have conducted an experimental study on mobile phones based on the process of consumer oriented Kansei Engineering. To determine how the mobile phone form elements can be combined to match a desirable simple–complex image, we have constructed a set of fuzzy rules. These fuzzy rules have been generated objectively based on the subjects' assessments in the experimental study. To justify this approach, we have compared the performance of the fuzzy logic model with other promising models such as NN and GRA-NN. The experimental result has demonstrated that the fuzzy logic model has a better performance. This suggests that the fuzzy logic approach is a promising methodological alternative for modeling the consumers' perception of a product characterized by a set of design elements. Although the mobile phones are used as a case study, the approach can be applied to other products with various design elements.

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