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A fuzzy CBR technique for generating product ideas

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Abstract

This paper presents a fuzzy CBR (case-based reasoning) technique for generating new product ideas from a product database for enhancing the functions of a given product (called the *baseline product*). In the database, a product is modeled by a 100-attribute vector, 87 of which are used to model the use-scenario and 13 are used to describe the manufacturing/recycling features. Based on the use-scenario attributes and their relative weights – determined by a fuzzy AHP technique, a fuzzy CBR retrieving mechanism is developed to retrieve product-ideas that tend to enhance the functions of the baseline product. Based on the manufacturing/recycling features, a fuzzy CBR mechanism is developed to screen the retrieved product ideas in order to obtain a higher ratio of valuable product ideas. Experiments indicate that the *retrieving-and-filtering* mechanism outperforms the prior *retrieving-only* mechanism in terms of generating a higher ratio of valuable product ideas.

Keywords: New product development; Case-based reasoning; Fuzzy CBR; Fuzzy AHP

1. Introduction

Product life cycle is getting shorter at this age. How to enhance the productivity of new product development is very important. A typical process of new product development includes product idea generation, conceptual design, detailed design, and economic justification of design. Among these procedures, generation of product ideas may be the most important because the other procedures are intended to realize and justify the generated ideas.

Various methods for creating product ideas have been published in the literature. According to the degree of computerization, the previous methods can be grouped into three categories: (1) manual-based approach, (2) computer-aided approach, and (3) computer-generated approach.

The manual-based approach is to generate product ideas by asking an individual or a group of people to think freely or think under a guided process. Examples of this approach include brainstorming method (Higgins, 1994; Nijssen & Lieshout, 1995; Osborn, 1963), forced relationships method (Higgins, 1994; Hisrich, Ingram, & Peters, 1991; Kotler, 1994), focus groups method (Higgins, 1994; Hisrich et al., 1991; Kotler, 1994; Nijssen & Lieshout, 1995), attribute listing method (Higgins, 1994; Kotler, 1994; Linda, 1991; Nijssen & Lieshout, 1995), check-list method (Higgins, 1994; Kotler, 1994), morphological analysis (Higgins, 1994; Kotler, 1994; Linda, 1991; Nijssen & Lieshout, 1995), and synectics method (Higgins, 1994; Kotler, 1994). Techniques of this approach are carried out *solely* through human, without using any computing facilities in the creation of new product ideas.

The computer-aided approach intends to use computer to guide a person's thinking process for creating or realizing product ideas. A typical technique of this approach encodes the innovative rules listed by TRIZ (Mann, 2003; Rantanen & Domb, 2002) in a computer program. Through a series of human–computer interaction activities, users of the computer program can find a number of design templates to realize a user-desired product function. Example software of the technique includes Goldfire Innovator (2006), Trisolver (2006), and Creax.com (2006).

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The computer-generated approach is intended to create ideas for enhancing the function of a *baseline* product by retrieving "scenario-compatible" products from database (Wu, Lo, & Hsu, 2006). The retrieved products are similar enough to the *baseline* product in the scenario where the *baseline* product is used. Product functions of the retrieved ones are called product ideas. This approach would generate a large amount of product ideas in a very short time. However, one weakness is that many less-valued products ideas may be generated, which would consequently require a large amount of human efforts to screen them.

To alleviate the weakness, this paper presents a CBR (case-based reasoning) technique combined with a fuzzy AHP method for retrieving product ideas that tend to be more-valued, and from the retrieved ones screening out those ideas that tend to be less-valued.

As shown in Fig. 1, the research framework involves three modules. The first module is to establish a product database in which a product is encoded by a vector involving 100 attributes. Of these attributes, 87 ones represent the scenario of using a product and the other 13 represent the scenario of manufacturing and recycling the product. Each attribute is defined by a linguistic variable of fuzzy theory (Zadeh, 1975).

The second module is to characterize the scenario of use for target customers. The 87 attributes for modeling the scenario of use are classified into five categories (also called dimensions). The technique of fuzzy AHP is used to determine the relative weight for each of the five dimensions in order to understand the preferences of target customers. The weighting of product attributes is intended to help retrieving more-valued products ideas; that is, less-valued ideas may not be generated in the retrieval stage.

The third module firstly retrieves product ideas whose functions tend to be attachable to the *baseline* product, and then filters out those retrieved ideas that tend to be less-valued. The retrieving mechanism is by using the 87 product attributes that have been weighted to characterize the scenario of use for target customers. The screening mechanism is by using the 13 manufacturing and recycling attributes.

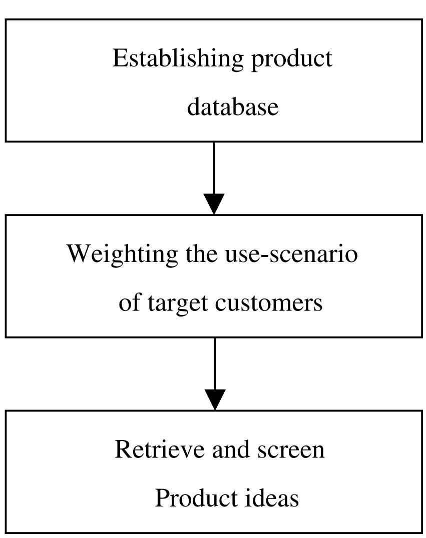

Fig. 1. Research framework.

The research framework is developed by examining the three main stages of a product life cycle – *manufacturing*, *using*, and *recycling*. The 100-attribute product representation for generating new product ideas are developed based on the various costs/benefits concerned in a product life cycle. We retrieve product ideas from the perspective of *enhancing the usability* in order to increase product value; and filter out product ideas from the perspectives of *reducing product cost* – reducing the manufacturing/recycling costs.

The remainder of this paper is organized as follows. Section 2 reviews the literature on case-based reasoning (CBR) technique. Section 3 describes the method for representing a product by a vector of 100 attributes. Section 4 presents the fuzzy AHP method for determining the relative weights to characterize target customers' scenario of use. Section 5 describes the CBR method for retrieving and screening product ideas. Experiment results are presented in Section 6 and concluding remarks are in Section 7.

2. Case-based reasoning

Case-based reasoning (CBR), a well-known artificial intelligence technique, is a process for solving a new problem case by referring to the solutions of similar past cases (Aamodt & Plaza, 1994; Kolodner & Leake, 1996; Marling, Sqalli, Rissland, Munoz–Avila, & Aha, 2002). In a CBR system, a database for storing the past cases has to be available. To solve a new problem case by CBR, similar past cases are first retrieved and their associated solutions are then used to aid users to develop solutions for the new case. Two survey papers of CBR can be referred to Watson and Marir (1994), de Mantaras and Plaza (1997).

A CBR system involves three modules: (1) a case representation scheme, (2) a similarity metric, and (3) a case-retrieval mechanism. A case representation scheme is to model a case by a set of attributes for characterizing the case at a particular application. A similarity metric is for measuring the similarity between any two cases. A case-retrieval mechanism is designed to retrieve the past cases that are similar enough to the new case.

To make a CBR system more user-friendly, some studies proposed a *fuzzy-CBR* approach. This approach advocates using linguistics variables in fuzzy theory to valuate the case attributes. A linguistic variable is represented by a natural language form as well as by a fuzzy number. The text description is intended to help users resolve the uncertainty issues while they valuate the case attributes. The fuzzy number representation and the associated fuzzy operators are used to calculate the similarity metrics for implementing the case-retrieving mechanism. Much literature based on such a fuzzy-CBR approach has been published.

Examples include Hirota et al. (1997), de Mantaras and Plaza (1997), Ruet and Geneste (2002), and Chan (2005).

The CBR paradigm has been applied in a wide variety of design problems. The applications include architecture design (Trousse & Visser, 1993), mechanical design (Maher & Garza, 1997), and some other design problems. In the CBR applications for product design, existing design architectures/parameters are retrieved to aid the realization of a product function (Bilgic & Fox, 1996; Maher, Balachandran, & Zhang, 1995) or to help engineers develop a new design that could fulfill the downstream requirements (Belecheanu, Pawar, Barson, Bredehorst, & Weber, 2003). These previous CBR studies for product design focus on the *engineering aspect* – realizing a design for a given functional requirement. Yet, this paper's focus – how to apply CBR to create new and marketable functional requirements for a given product is rarely studied.

3. Product database

In the product database for generating and screening ideas, a product is encoded by a vector consisting of 100 attributes, where 87 ones are used to characterize the scenario of using the product, and 13 attributes are used to describe the manufacturing and recycling characteristics. For a product, each attribute is described by a linguistic variable in fuzzy theory.

3.1. Product attributes for creating ideas

This research generates new product ideas based on the following *hypothetical assertion* – two products that are similar in their scenario of use have chance to be combined into a new product. That is, the new product would involve the main functions of the two products. To generate new product ideas for a given product (called the *baseline* product), we aim to identify some other products that are similar to the baseline product in its scenario of use.

This research models a product use-scenario from five dimensions, which are developed based on the notion of UCD (user centered design) – a design paradigm originally proposed by Norman and Draper (1986). The UCD notion advocates that a product should be designed based on the user's needs and the scenario where they use the product. As shown in Fig. 2, the five dimensions involve: *interface attributes*, *task type*, *physical feature*, *environment*, and *user characteristic characteristics*; and they are deployed into 20 sub-dimensions (also called groups) that ultimately yield 87 attributes (Table 1).

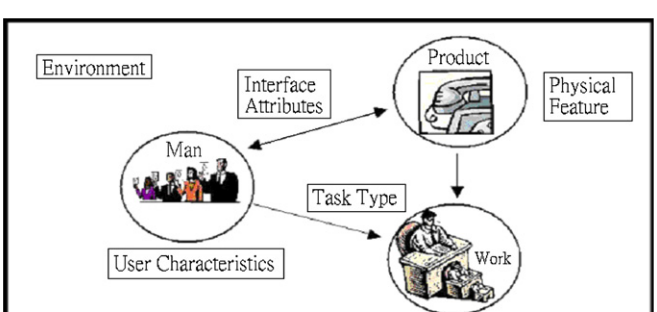

Fig. 2. The proposed product representation is based on a UCD paradigm.

The first dimension – *interface attributes* are to identify the medium through which the product interacts with the user. Here, the medium denotes a particular portion of the user's body. This research classifies the interface attributes into three groups: *sensory modality*, *response modality*, and *interface point*. The interface attributes are composed of 18 attributes in total.

The second dimension – *task type* is to model the tasks to be performed by the user through using the product. According to users' needs, the tasks are categorized into seven groups: *eating*, *clothing*, *living*, *transportation*, *education/entertainment*, *working*, and *health care*. These seven groups are further characterized by 30 attributes based on the execution process in each group.

The third dimension – *physical feature* is intended to describe a product from the aspects of *physical size*, *mobility*, and *scaleability*. Ten attributes are used to model the dimension of physical feature.

The fourth dimension – *environment* is intended to characterize the environment where the product is used. The characterization involves three groups: *sociality*, *physical place*, and the *harshness of environment*. Ten attributes are used to model the environment dimension.

The fifth dimension – *user characteristics* are intended to describe which groups of users tend to use the product. The dimension is characterized by the following demographic features: *gender*, *age*, *profession*, and *job title*. These five features are further described by 19 attributes.

3.2. Product attributes for screening ideas

Based on the aforementioned product modeling method, new product ideas of the baseline product may be retrieved by applying the fuzzy CBR technique. Surely, a retrieved product idea and the baseline product to a certain extent are "compatible", from the perspective of *using* the two products. However, from the perspectives of *manufacturing/recycling*, these two products may not be economically justifiable to combine them into one. That is, we assert that a product idea will be discarded, if it has few commonality with the baseline product in terms of manufacturing/recycling attributes.

As shown in Table 1, 13 attributes are used to model the features of manufacturing and recycling, which are grouped into four groups.

The first group describes the materials of a product, which involves the following four types: (a) metal, (b) non-metal, (c) animals, and (d) plants. A product may be composed of several types of materials. The percentage of a particular type of material used in a product is described by an attribute.

Table 1
Product representation for cell phones and ball pens

ID	Dimension	Group	Attribute	Cell phone	Ball pen
1	Interface attributes $\hat{W}_1 = 0.1540$	Sensory modality	Visualization (or *sight*)	(0.25, 0.5, 0.75)	(0.75, 1.0, 1.0)
2			Audition	(0.75, 1.0, 1.0)	(0.0, 0.0, 0.25)
3			Gustatory (or *tasting*)	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
4			Olfactory (or *smelling*)	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
5			Tactile	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
6		Response modality	Eye	(0.25, 0.5, 0.75)	(0.75, 1.0, 1.0)
7			Mouth	(0.75, 1.0, 1.0)	(0.0, 0.0, 0.25)
8			Face	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
9			Neck	(0.25, 0.5, 0.75)	(0.0, 0.0, 0.25)
10			Hand	(0.75, 1.0, 1.0)	(0.75, 1.0, 1.0)
11			Foot	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
12			Finger	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
13		Interface point	Head	(0.0, 0.0, 0.25)	(0.0, 0.25, 0.5)
14			Neck-shoulder	(0.0, 0.25, 0.5)	(0.0, 0.0, 0.25)
15			Chest-waist	(0.75, 1.0, 1.0)	(0.75, 1.0, 1.0)
16			Back	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
17			Hand	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
18			Foot	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
19	Task type $\hat{W}_2 = 0.3588$	Eating	Preparation	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
20			Processing	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
21			Serving	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
22			Cleaning	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
23		Clothing	Preparation	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
24			Modification	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
25			Cleaning	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
26		Living	Cleaning	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
27			Maintenance	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
28			Monitoring	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
29			Decorating	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
30		Transportation	Planning	(0.25, 0.5, 0.75)	(0.75, 1.0, 1.0)
31			Navigating	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
32			Monitoring	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
33			Emergency handling	(0.75, 1.0, 1.0)	(0.0, 0.0, 0.25)
34			Vehicle	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
35		Education/entertainment	Searching	(0.25, 0.5, 0.75)	(0.0, 0.0, 0.25)
36			Understanding/integrating	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
37			Creating	(0.25,0.5,0.75)	(0.75, 1.0, 1.0)
38			Storing/ distributing	(0.0, 0.25, 0.5)	(0.0, 0.0, 0.25)
39			Article	(0.0, 0.25, 0.5)	(0.5, 0.75, 1.0)
40		Working	Planning	(0.0, 0.25, 0.5)	(0.75, 1.0, 1.0)
41			Execution	(0.25, 0.5, 0.75)	(0.0, 0.25, 0.5)
42			Inspection/review	(0.0, 0.0, 0.25)	(0.25, 0.5, 0.75)
43			Decision	(0.0, 0.25, 0.5)	(0.0, 0.0, 0.25)
44			Communication	(0.75, 1.0, 1.0)	(0.0, 0.25, 0.5)
45		Health care	Daily maintenance	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
46			Detection/diagnosis	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
47			Remedy	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
48			Rehabilitation	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
49	Physical feature $\hat{W}_3 = 0.1485$	Physical size	Mini	(0.0, 0.25, 0.5)	(0.0, 0.25, 0.5)
50			Small	(0.5, 0.75, 1.0)	(0.5, 0.75, 1.0)
51			Medium	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
52			Large	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
53			Extra-large	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
54		Mobility	Portable	(0.75, 1.0, 1.0)	(0.75, 1.0, 1.0)
55			Stationary	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
56		Scaleability	Mall	(0.0, 0.0, 0.25)	(0.25, 0.5, 0.75)
57			Medium	(0.75, 1.0, 1.0)	(0.25, 0.5, 0.75)
58			Large	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)

(*continued on next page*)

Table 1 (*continued*)

ID	Dimension	Group	Attribute	Cell phone	Ball pen
59	Environment $\hat{W}_4 = 0.1520$	Sociality	Single user	(0.75, 1.0, 1.0)	(0.75, 1.0, 1.0)
60			Group users	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
61		Physical place	Indoor	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
62			Outdoor	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
63		The harshness of environment	Illumination	(0.25, 0.5, 0.75)	(0.5, 0.75, 1.0)
64			Temperature	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
65			Humidity	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
66			Noise/vibration	(0.0, 0.25, 0.5)	(0.25, 0.5, 0.75)
67			Dust	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
68			Pressure	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
69	User characteristics $\hat{W}_5 = 0.1867$	Gender	Male	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
70			Female	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
71		Age	Infant	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
72			Child	(0.0, 0.25, 0.5)	(0.0, 0.0, 0.25)
73			Teenager	(0.25, 0.5, 0.75)	(0.0, 0.25, 0.5)
74			Young adult	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
75			Adult	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
76			The aged	(0.0, 0.25, 0.5)	(0.0, 0.25, 0.5)
77		Profession	Agriculture	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
78			Manufacturing	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
79			Trade	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
80			Service/education	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
81			Government	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
82		Job title	Top management	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
83			Middle management	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
84			Supervisor	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
85			Engineer	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
86			Office clerk	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
87			Operator	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
88	Manufacturing and recycling	Material processing mechanism	Metal	(0.0, 0.25, 0.5)	(0.0, 0.25, 0.5)
89			Nonmetal	(0.75, 1.0, 1.0)	(0.75, 1.0, 1.0)
90			Animals	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
91			Plants	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
92		Processing mechanism	Physics	(0.75, 1.0, 1.0)	(0.75, 1.0, 1.0)
93			Chemistry	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
94			Biology	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
95		Energy resources	Electricity	(0.0, 0.25, 0.5)	(0.0, 0.0, 0.25)
96			Batteries	(0.75, 1.0, 1.0)	(0.0, 0.0, 0.25)
97			Solar energy	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
98			Oil/gas	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.25)
99		Recycling	Easiness	(0.75, 1.0, 1.0)	(0.5, 0.75, 1.0)
100			Usability	(0.75, 1.0, 1.0)	(0.0, 0.25, 0.5)

The second group describes the processing mechanisms, which involves three types: (a) physical processes, (b) chemical processes, and (c) biological processes. A product may be manufactured by more than one type of processes. The percentage of a particular type of process used to manufacture a product is described by an attribute.

The third group describes the energy resources used in a product, which involves four types: (a) electricity, (b) batteries, (c) solar energy, and (d) oil/gas. A product may use more than one type of energy resources. The percentage of energy resources used by a product is described by an attribute.

The fourth group uses two attributes model the processes and results of recycling a product, which involves (a) the easiness in recycling a product, and (b) the usability of a recycled product. The easier is a recycling process, the higher is its attribute value; the higher is the usability of a recycled product, the higher is its attribute value.

3.3. Linguistic variables for describing product attributes

To facilitate users to characterize a product, each of the 100 product attributes is described by a linguistic variable in fuzzy theory. A linguistic variable, appearing in a natural language form, represents a human's judgment, which can be further modeled by a triangular fuzzy number (Zadeh, 1975).

Of the 100 product attributes, the first 98 attributes are described by five linguistic variables: *extreme relevance*, *high relevance*, *relevance*, *low relevance*, and *no relevance*. The associated fuzzy number of a linguistic variable, $\tilde{A} = (l_1, m_1, r_1)$, is shown in Fig. 3, where l_1 denotes the

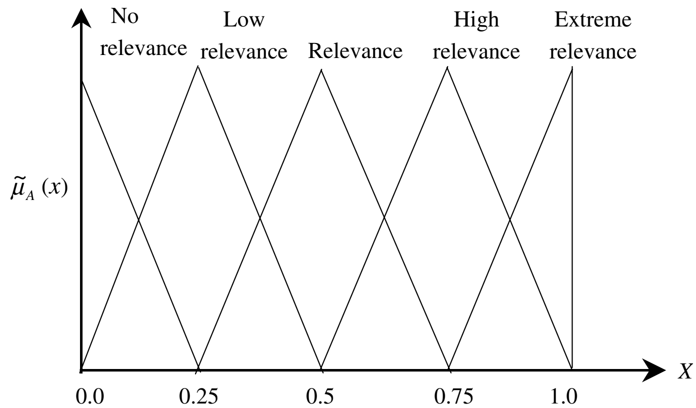

Fig. 3. Linguistic variables and the associated fuzzy numbers.

leftmost coordinate, m_1 is the central coordinate, and r_1 the rightmost coordinate on the x-axis (Moon & Kang, 2001). The last two attributes (attribute 99 and 100), which characterize the recycling characteristics, are described by another five linguistic variables: *very high*, *high*, *normal*, *low*, and *very low*. The fuzzy numbers in Fig. 3 are also used to represent these linguistic variables.

4. Weighting each dimension of target customers' use-scenario

In retrieving product ideas, we have to determine the relative importance of the five dimensions of target customers' use-scenario. To resolve the vagueness caused by human judgment, we use a widely used methodology – fuzzy AHP (analytical hierarchy process) to determine the weighting for each of the five dimensions.

The computational procedure of the fuzzy AHP methodology (Zadeh, 1975) is summarized below, where the arithmetical operators of fuzzy numbers are defined in Appendix 1.

Step 1: Define linguistic variables for pair-wise comparison.
We use linguistic variables to compare the relative importance between any two dimensions. These linguistic variables include "absolutely important", "very strongly important", " essentially important", "weakly important" and "equally important" on a five level scales, where between any two consecutive scales an intermediate scale is additionally defined so that 9 scales are created. Table 2 shows the resulting 9 scales that are represented by 9 triangular fuzzy numbers (Chiou, Tzeng, & Cheng, 2005): $\tilde{1}, \tilde{2}, \ldots, \tilde{9}$.

Step 2: Establish the comparison matrix $\tilde{A}$.
By performing a pair-wise comparison for any two of the five concerned dimensions, a fuzzy matrix $\tilde{A}$ is constructed.

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & 1 \end{bmatrix}$$

where
if $i = j,\ \tilde{a}_{ij} = 1$,
if $i \neq j,\ \tilde{a}_{ij} = \tilde{a}_{ji}^{-1}$ and $\tilde{a}_{ij} = (\tilde{a}_{ij}^1 \oplus a_{ij}^2 \oplus \cdots \oplus \tilde{a}_{ij}^N)/N$
$\tilde{a}_{ij}^k$: customer k's judgment on the relative importance between dimension i and j
N: total number of target customers interviewed.

Step 3: Calculate the fuzzy weight of each row in $\tilde{A}$ (Buckley, 1985).

$$\tilde{Z}_i = (\tilde{a}_{i1} \otimes \tilde{a}_{i2} \otimes \cdots \otimes \tilde{a}_{in})^{\frac{1}{n}} \quad \forall i = 1, 2, \ldots, n$$
$$\tilde{W}_i = \tilde{Z}_i \otimes \left(\tilde{Z}_1 \oplus \tilde{Z}_2 \oplus \cdots \oplus \tilde{Z}_n\right)^{-1} \quad \forall i = 1, \ldots, n$$

Step 4: Defuzzication of $\tilde{W}_i$ and $\tilde{A}$ (Teng & Tzeng, 1993).

$$a_{ij} = Defuzzy(\tilde{a}_{ij})$$
$$W_i = Defuzzy(\tilde{W}_i)$$

where the function *Defuzzy* is stated in Appendix 1.

Table 2
Linguistic variables used in the fuzzy AHP

Fuzzy number	Linguistic variables
$\tilde{1} = (1, 1, 1)$	Equally important
$\tilde{3} = (2, 3, 4)$	Weakly important
$\tilde{5} = (4, 5, 6)$	Essentially important
$\tilde{7} = (6, 7, 8)$	Very strongly important
$\tilde{9} = (8, 9, 10)$	Absolutely important
$\tilde{2} = (1, 2, 3);\ \tilde{4} = (3, 4, 5);\ \tilde{6} = (5, 6, 7);\ \tilde{8} = (7, 8, 9)$	Intermediate values between two adjacent judgments

Table 3
Values of RI

n	1	2	3	4	5	6	7	8	9	10	11
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51

Step 5: Normalization of W_i

$$\hat{W}_i = \frac{W_i}{\sum_{i=1}^{n} W_i}.$$

Step 6: Consistency check.

(1) Compute W_i^* as follows:

$$A \cdot \begin{bmatrix} \tilde{W}_1 \\ \tilde{W}_2 \\ \vdots \\ \tilde{W}_n \end{bmatrix} = \begin{bmatrix} W_1^* \\ W_2^* \\ \vdots \\ W_n^* \end{bmatrix}$$

where $A = [a_{ij}]$.

(2) Compute

$$\lambda_{\max} = \frac{1}{n}\left[\left(\frac{W_1^*}{\hat{W}_1}\right) + \left(\frac{W_2^*}{\hat{W}_2}\right) + \cdots + \left(\frac{W_n^*}{\hat{W}_n}\right)\right]$$

where $\lambda_{\max}$ is called maximum eigenvalue.

(3) Compute

$$CI = \frac{\lambda_{\max} - n}{n-1}$$

where CI is called consistency index.

(4) Compute $CR = CI/RI$, where CR is called consistency ratio, and RI is called the average random consistency index of randomly generated matrices of size $n \times n$. The values of RI have been provided by Saaty (1980) as shown in Table 3.

(5) Consistency check.
If $CR \leqslant 0.1$, then the pair-wise comparison matrix is reasonably consistent and $\widehat{W}_i$, $1 \leqslant i \leqslant n$, is the resulting weighting of dimension i. If $CR > 0.1$, then the pair-wise comparison results are inconsistent and the pair-comparison procedure has to be updated.

Notice that $\widehat{W}_i$, $1 \leqslant i \leqslant 5$, is the weighting factor of dimension i in the product representation. The five dimensions include 87 use-scenario attributes. The attributes in each dimension are of the same weighting – the weight of their parent dimension. Let w_j represent the weighting factor of attribute j. Then, $w_j = \widehat{W}_i$ if attribute j belongs to dimension i. In summary, the results of the fuzzy AHP yield the weighting of each use-scenario attribute (w_j, $1 \leqslant j \leqslant 87$).

5. Retrieving and filtering product ideas

Given a product database, this research uses two mechanisms to propose new product ideas for enhancing the functions of a *baseline* product. Firstly, from the database, we retrieve products that tend to be compatible to the *baseline* product – from the perspective of *product usability*. Secondly, we filter out the retrieved products whose combinations with the baseline product tend to become costly – from the perspective of *manufacturing and recycling*.

The retrieving and filtering mechanisms are explained by referring to a scenario stated below. A product database $P = \{P_i,\ i = 1, \ldots, K\}$ has been established, where K is a huge positive integer number and $P_i = [\tilde{p}_{ij}]$, $1 \leqslant j \leqslant 100$, denotes the vector representation of product i. Let $B = [\tilde{b}_j]$, $1 \leqslant j \leqslant 100$, represents the *baseline* product. Notice that $\tilde{p}_{ij}$ and $\tilde{b}_j$ are fuzzy numbers that indicate the attributes of a product. The purpose is to retrieve some products from database P, whose combinations with *baseline* product B may enhance the resulting product usability in a low-cost manner.

5.1. Retrieving mechanism

The procedure of the retrieving mechanism is described below.

Step 1: Define a *retrieving threshold* $H_r \in [0,1]$.

Step 2: Identify the important attributes of the *baseline* product $B = [\tilde{b}_j]$, $1 \leqslant j \leqslant 100$.
$S = \{j | \tilde{b}_j$ is of high relevance or extreme relevance$\}$ (Refer to Fig. 3).
Let $N(S)$ denote the number of attributes in set S.

Step 3: Form retrieval key sets.
Ask users to randomly cluster the attributes in S into several subsets T_k, $1 \leqslant k \leqslant q = \lceil N(S)/m \rceil$, where each subset involves m or $(m-1)$ attributes. That is, $S = \bigcup_{k=1}^{q} T_k$, where subset T_k is called a *retrieval key set*.

Step 4: With respect to the retrieval key set T_k, compute *product relevance metric* between products $P_i = [\tilde{p}_{ij}]$ and *baseline* product $B = [\tilde{b}_j]$.

$$\tilde{R}_i^{T_k} = \sqrt{\frac{\sum_{j \subset T_k} [\tilde{b}_j \otimes R(\tilde{b}_j, \tilde{p}_{ij}) \otimes w_j]^2}{\sum_{j \subset T_k} [b_j \otimes w_j]^2}}$$

for $k = 1, 2, \ldots q$

where w_j is the weighting factor of attribute j as derived in Section 4, $R(\tilde{b}_j - \tilde{p}_{ij})$ as defined below represents the *relevance metric of jth attribute* between *baseline* product B and product P_i.

$$R(\tilde{b}_j, \tilde{p}_{ij}) = 1 - |\tilde{b}_j - \tilde{p}_{ij}|$$

Step 5: Defuzzication of $\tilde{R}_i^{T_k}$

$$R_i^{T_k} = Defuzzy(R_i^{T_k}) \quad \text{for } k = 1,\ldots,q$$

Step 6: Retrieve products compatible to*baseline* product B from database P.

$$Q_k = \{P_i | R_i^{T_k} \geqslant H_{\mathrm{r}}\}$$
$$Q = \bigcup_{k=1}^{q} Q_k$$

where Q represents the set of retrieved products.

Several distinct points in the retrieving mechanism are explained further. First, only *important* attributes in *baseline* product B are included in a retrieval key set. Experiments indicate that the inclusion of less important attributes would lead to the retrieval of a huge number of products that are irrelevant to *baseline* product B. Second, a retrieval key set involves only a *few number* of important attributes. With the inclusion of all important attributes in a retrieval key set, the number of retrieved products tends to be very small; and their functions tend to be too close to the *baseline* product B and cannot be seen as a good product idea. Third, in the computation of $\tilde{R}_i^{T_k}$, $\tilde{b}_j$ denotes the value of jth attribute and w_j denotes its relative importance from the perspective target customer. That is, $\tilde{b}_j$ is independent of target customers while w_j is dependent on target customers.

5.2. Filtering mechanism

The retrieved products in set Q are *relevant* to the baseline product B, from the perspective of *usability*. However, some of these products may not be compatible to product B from the perspectives of manufacturing and recycling. We use a filtering mechanism to filter out these incompatible products in Q. The procedure of the filtering mechanism is described below.

Step 1: Define a *filtering threshold*, $H_{\mathrm{f}} \in [0,1]$.
Step 2: Define the filtering key set T_m, $m = 1,\ldots,4$.
As stated in Section 3, we use 13 attributes (attributes 88–100) to model the features of manufacturing and recycling, which are grouped into four categories. The attributes in mth category forms a filtering key set, denoted by T_m.
Step 3: Compute compatible metric between product P_i and B, with respect to T_m.

$$\tilde{C}_i^{T_m} = \sqrt{\frac{\sum_{j\subset T_m}[\tilde{b}_j \otimes R(b_j, p_{ij})]^2}{\sum_{j\subset T_m}[\tilde{b}_j]^2}}$$

for $m = 1, 2, \ldots 4$

where $R(\tilde{b}_j, \tilde{p}_{ij}) = 1 - |\tilde{b}_j - \tilde{p}_{ij}|$.
Step 4: Defuzzication of $\tilde{C}_i^{T_m}$

$$C_i^{T_m} = Defuzzy(\tilde{C}_i^{T_m}), \quad \text{for } m = 1,\ldots,4$$

Step 5: Filter out the incompatible products from set Q

$$F_m = \{P_i | C_i^{T_m} < H_{\mathrm{f}}\}$$
$$F_f = \cup_{m=1}^{4} F_m$$

where F_f represents the set of incompatible products in set Q.
Step 6: Determine X, the set of products that may enhance the function of product B effectively

$$X = Q - F_f.$$

6. Experiments

An empirical study is carried out to compare the efficiency and effectiveness between the proposed *retrieving-and-filtering* mechanism and the *retrieving-only* mechanism published in Wu et al. (2006) that has been justified to be better than the traditional brainstorming approach. Two experiments for the comparison are performed; one experiment uses cell phone and the other uses ball pen as the *baseline* products.

A prototype product database is established for the experiments, which involves 1600 products and is coded by Microsoft Access. The *retrieving/filtering* mechanism is coded by ASP.NET (Active Server Page.NET), with its interface developed by Macromedia Dreamwaver, and Microsoft Internet Explorer is used as the vehicle for web browsing.

To determine the dimensional weighting of target customers' use-scenarios, 30 female subjects, aged 19–30, are invited to perform the pair-wise comparison required by the fuzzy AHP method. Results and the associated data of the AHP process are listed in Table 4.

6.1. Generating product ideas

Five senior undergraduate students are invited as experiment subjects. Using cell phone as the *baseline* product, each step in executing the *retrieving-and-filtering* mechanism is explained below.

Step 1: Set the *retrieving threshold*, $H_{\mathrm{r}} = 0.5$.
Step 2: Of the 87 product attributes of a cell phone, 10 attributes are automatically identified as important attributes (highlighted in Table 1).

Table 4
Detailed data in the fuzzy AHP for characterizing target customers, where $CI = 0.08199$ and $CR = 0.07321$

Dimension	$\tilde{W}_i$	W_i	$\hat{W}_i$
Interface attributes	(0.10499, 0.15366, 0.22404)	0.160896	0.1540
Task type	(0.25824, 0.36120, 0.50480)	0.374747	0.3588
Physical feature	(0.10252, 0.14837, 0.21435)	0.155079	0.1485
Environment	(0.10462, 0.15165, 0.21995)	0.158739	0.1520
User characteristics	(0.12496, 0.18512, 0.27504)	0.195040	0.1867

Step 3: From the 10 important attributes, each subject is asked to freely form four retrieval key sets; each set involves either 3 or 2 attributes.
Step 4: Based on the retrieval key sets, the *retrieving* mechanism will generate a set Q – the set of retrieved products.
Step 5: Set the *filtering threshold*, $H_f = 0.5$.
Step 6: Based on the four filtering key sets, the *filtering* mechanism automatically identifies a set F_f that represents the incompatible products in set Q.
Step 7: The system computes the set $X = Q - F_f$.

In the aforementioned procedure, set X represents the product ideas proposed by the *retrieving-and-filtering* mechanism and set Q represents the product ideas proposed by the *retrieving-only* mechanism.

6.2. Comparison of product-idea-generating mechanisms

The performance metric for comparing the two product-idea-generating mechanisms is called *creative ratio*, as defined below.

$$C_Z = \frac{N(Z_g)}{N(Z)}$$

where Z represents a set of product ideas, Z_g is a subset of Z that includes only good product ideas, and $N(Z)$ represents the number of product ideas in set Z.

The objectives of the experiments are to compare the value of C_X and C_Q (Table 5). As stated, X is a subset of Q. A *random filtering* mechanism would filter out good product-ideas at a probability of C_Q; this on average yields that $C_X = C_Q$. By contrast, a *less-effective filtering* mechanism would yield that $C_X < C_Q$, while an *effective filtering* mechanism would yield that $C_X > C_Q$. That is, $C_X > C_Q$ indicates that the average time required to identify one good product-idea is less.

The method for justifying whether a product-idea is good is through expert's evaluation. Three experts familiar with new product developments are invited to evaluate the generated product-ideas based on three criteria – *originality*, *valuableness*, and *usefulness* (Besemer & O'Quin, 1986). Each criterion is rated in a five-point scale – the higher the better. A product-idea is justified by averaging the points of the three criteria; an average point greater than 4.0 is regarded as a good idea.

The results of the two experiments are shown in Table 5. For each baseline product, the mean of C_X is greater than that of C_Q. A t-test for cell phone ($\alpha = 0.05$, t-value = -7.641, and P-value = 0.002) indicates $C_X > C_Q$ is statistically significant. Another t-test for ball pen ($\alpha = 0.05$, t-value = -5.287, and P-value = 0.006) also supports the finding $C_X > C_Q$. These two findings conclude that the proposed *filtering* mechanism is effective. That is, the average time required to *manually identify* one good product-idea from the retrieved products is reduced if we enhance the *retrieving* mechanism by a *filtering* mechanism.

However, the advantage of $C_X > C_Q$ is offset by a drawback – $N(Q_g) > N(X_g)$. That is, some good product-ideas are filtered out in the filtering mechanism. One may question that what is the "*net benefit*" of developing the filtering mechanism. Is the "*net benefit*" positive or negative? Consider the comparison of the *retrieving* mechanism and an *exhaustively-listing* mechanism – taking all products in the database as generated product-ideas. Surely, the *exhaustively-listing* mechanism can always generate more numbers of good ideas than the retrieving mechanism, at the expense of paying more expert time to identify good product ideas. This analogy illustration may explain the need for developing an effective filtering mechanism.

Moreover, the performance of the filtering mechanism can be regulated by giving different values to the *filtering threshold* (H_f). In the case of $H_f = 0$, the filtering mechanism is halted; that is, only the retrieving-mechanism works. Increasing the value of H_f tends to pay more attention to the filtering mechanism. Users of the product-idea-generating systems may iteratively give different H_f value, depending upon the number of retrieved ideas and how much expert time is available to evaluate these ideas. Suppose an initial assignment of $H_f = 0.3$ yields 1 million product-ideas. This would lead the users to reassign a higher H_f value to reduce the numbers of the retrieved ideas.

Table 6 gives 23 product-ideas for enhancing the function of cell phone. Table 7 describes 18 product-ideas for enhancing the function of ball pen. To our knowledge, some of these ideas for enhancing the baseline products are currently not available in the market.

Table 5
Comparing the performance of the *retrieving-and-filtering* and the *retrieving-only* mechanisms

	Cell phone						Ball pen					
	Retrieving			Retrieving + filtering			Retrieving			Retrieving + filtering		
	$N(Q)$	$N(Q_g)$	C_Q (%)	$N(X)$	$N(X_g)$	C_X (%)	$N(Q)$	$N(Q_g)$	C_Q (%)	$N(X)$	$N(X_g)$	C_X (%)
Sub_1	302	30	9.93	134	23	17.16	225	22	9.78	108	17	15.74
Sub_2	179	21	11.73	82	17	20.73	219	18	8.22	114	12	10.53
Sub_3	254	24	9.45	119	16	13.44	247	23	9.31	139	18	12.95
Sub_4	254	26	10.23	98	18	18.37	211	18	8.53	94	11	11.70
Sub_5	207	26	12.56	104	19	18.27	198	15	7.58	78	11	14.10
Mean	239	25.4	11.02	107	18.6	17.76	220	19.2	8.73	106.6	13.8	12.95

Table 6
Generated product ideas for cell phone

Alcohol tester	MP3	Language learning machine
Pulse detector	e-Map	PDA (personal digital assistant)
Radio and Walkman	RFID	Mosquito prevention set
Electronic pet (Game)	e-Book	USB Flash memory drive
Stun gun for security	Cosmetic box	Language translator/Dictionary
Anti-camera detector	Pedometer	Remote controller for door/car
Clinical thermometer	Digital wallet	OBU (car navigation system)
Barcode scanner	Strobe light	

Table 7
Generated product ideas for ball pen

Lipstick	Compass	Clinical thermometer
Laser pointer	Baton	Electric torch
Eyebrow pencil	Mp3	Ultraviolet rays tester
Massage stick	GPRS	USB Flash memory drive
Voice recorder	Pill box	Pregnancy test pen
Swatch (Timer)	LED	Language translator

7. Concluding remarks

This research presents a *case-based reasoning* (CBR) approach combined with the fuzzy AHP method to generate new product ideas that tend to be valuable for enhancing the baseline product. The generation of new product ideas is through a *retrieving-and-filtering* mechanism operated on a product database, where a product is modeled by 100 attributes—87 ones model the *use-scenario* and the other 13 model the *manufacturing-and-recycling* features.

The retrieving mechanism is a fuzzy CBR technique that utilizes the *use-scenario* attributes for retrieving product-ideas. The retrieved product-ideas are subsequently screened by a filtering mechanism – a CBR technique that utilizes the *manufacturing-and-recycling* attributes as the filtering criteria. The filtering mechanism is proposed to filter out less valuable product ideas in order to save time for subsequent product-idea evaluation by experts.

A prototype system has been implemented for justifying the contribution of the filtering mechanism. Experiments show that the *retrieving-and-filtering* mechanism outperforms the prior *retrieving-only* mechanism in terms of creative ratio. That is, the *retrieving-and-filtering* mechanism generates higher percentage of "good product ideas" as opposed to that of the *retrieving-only* mechanism.

Appendix 1. Arithmetical operators for fuzzy numbers

The fuzzy arithmetic operators used in this research are defined below (Laarhoven & Pedrycz, 1983; Zadeh, 1975), by referring two fuzzy numbers $\tilde{a}_1 = (l_1, m_1, r_1)$ and $\tilde{a}_2 = (l_2, m_2, r_2)$.

(1) Addition operator: $\oplus$

$$\tilde{a}_1 \oplus \tilde{a}_2 = (l_1 + l_2, m_1 + m_2, r_1 + r_2)$$

(2) Subtraction operator: $-$

$$\tilde{a}_1 - \tilde{a}_2 = (l_1 - l_2, m_1 - m_2, r_1 - r_2)$$

(3) Multiplication operator: $\otimes$

$$\tilde{a}_1 \otimes \tilde{a}_2 = (l_1 \times l_2, m_1 \times m_2, r_1 \times r_2)$$

(4) Division operator: /

$$\tilde{a}_1 / \tilde{a}_2 = \left(\frac{l_1}{r_2}, \frac{m_1}{m_2}, \frac{r_1}{l_2} \right)$$

(5) Inverse power operators

$$\tilde{a}_1^{-1/n} = (r_1^{-1/n}, m_1^{-1/n}, l_1^{-1/n})$$

(6) Distance of two fuzzy numbers (Chen, 2000)

$$D(\tilde{a}_1, \tilde{a}_2) = \left\{ \sqrt{1/3[(l_1 - l_2)^2 \oplus (m_1 - m_2)^2 \oplus (r_1 - r_2)^2]} \right\}$$

(7) Defuzzication operator (Teng & Tzeng, 1993)

$$Defuzzy(\tilde{a}_1) = |(r_1 - l_1) + (m_1 - l_1)|/3 + l_1$$

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