Understanding Customers' Affective Needs with Linguistic Summarization

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Abstract: To increase the chance of launching a successful product into market, it is essential to satisfy customers' affective needs during the product design stage. However, understanding customers' affective needs is very difficult task and product designers might misunderstand the customers' affective needs. In this study, linguistic summarization with fuzzy set is used to present customers' affective needs with natural language statements which could be easily understood by human beings. The relations between customers' affective needs and product design elements are represented by type-I and type-II fuzzy quantified sentences. To illustrate the applicability of the linguistic summarization with fuzzy set in translating customers' affective needs to natural language statements, a case study is conducted on mobile phone design. The results indicate that the linguistic summarization with fuzzy set can be a useful tool to assist designers to create products satisfying affective needs of customers.

Keywords: Affective Design, Linguistic Summarization, Fuzzy Sets.

1. INTRODUCTION

With the fierce competition in market environment, satisfying the customer needs on product has become one of the most important factors in product development for almost all companies. Considering the fact that the mass customization and personalization have been recognized as a key factor for companies to gain competitive advantages (Jiao, Zhang, & Helander, 2006). The functional and affective needs have been undoubtedly accepted as the primary importance for satisfying the customer needs. Since there are many similar products which are functionally equivalent with the progress in product design technologies, it is very difficult to differentiate them based only on their functional attributes (Khalid & Helander, 2004; Shi, Sun, & Xu, 2012). Furthermore, design in terms of usability and performance has not been seen as competitive advantage because nearly all companies have same technologies. Thus, it is necessary to design products considering the customers' affective needs so that differentiating among them is possible.

The affect is defined as customer's psychological response to the perceptual design details of the product (Demirbilek & Sener, 2003). Affective design is the inclusion or representation of affect (e.g.

emotions, subjective impressions, visual perceptions, etc.) in the design processes (Khalid & Helander, 2004). The main challenge for affective design is to accurately grasp the customer's affective needs and subsequently to design products to meet those needs (Bahn, Lee, Nam, & Yun, 2009). Many studies have worked on how to measure and analyze human reactions to affective design and how to assess the corresponding affective design features. However, capturing the customers' affective needs is sometimes very hard owing to their linguistic origins. Affective needs are imprecise as they include subjective impressions, very hard to transform into verbal descriptions. In some cases, to express their affective needs on product, customers and designers might use different sets of context. These differences in semantics and terminology could lead to the inconsistency in transferring affective needs effectively from customers to designers (Jiao et al., 2006).

There have been reported a plenty number of studies to analyze relations between affective needs of customers and product design elements. Especially, Kansei Engineering (KE) has been introduced as a methodology for translating the customer's affective needs on a product into the design elements of the product (Nagamachi, 1995). KE has been successfully implemented in affective design so as to express the relationship between the affective needs of the customers and the design elements of the product. The relationship between affective needs of customers and product design elements has also been dealt with in a wide range of approaches. Han et al. (2000; 2004; 2001) identified most important design elements along with the predicted effect on usability by employing empirical models, e.g., multivariate linear regression techniques. Methods such as linear regression could only handle linear relations; and they are therefore not capable of effectively dealing with nonlinear relations. To deal with the nonlinearity between affective needs of customers and product design elements, the soft computing techniques such as fuzzy set (FS), artificial neural networks (ANN) and so on have been used. The relationships between the affective user needs and product design variables were examined by FS and fuzzy rule based models by Hsiao (1994), Kwon (1999) and Akay and Kurt (2009). In addition to above works, a few studies have implemented ANN with other soft computing techniques in product design. Hsiao and Huang (2002) used an ANN model to analyze the relationship between product form parameters of a chair and image perception of the product using several adjective pairs. Hsiao and Tsai (2005) developed a hybrid modeling approach based on fuzzy ANN and genetic algorithm (GA) for automatic design of product forms. By considering color parameter as well as design form parameters, ANN and grey theory (GT) were used to predict the image sensation of a product based on a given input set of form and color parameters, respectively (Tsai, Hsiao, & Hung, 2006). Lai et al. (2005) used Grey Prediction and ANN models to find optimal design combinations of product form parameters of mobile phones satisfying a desired product image represented by semantic word pairs. Lai et al. (2006) extended their previous product image study on product form by incorporating product color factor using Quantitative Theory Type I and ANNs. Yanagisawa and Fukuda (2005) proposed an interactive reduct evolutional computation system for aesthetic design of products. Poirson et al. (2007) employed a GA to explore the best design parameters enhancing perceived quality of brass musical instruments measured with a sensory attribute intonation. Chang et al. (2007) developed a comprehensive model of form attractiveness for exploring the attractiveness of passenger car forms aimed at young customers. Lin et al. (2007) developed a fuzzy logic approach to determine the best combination of mobile phone form elements for matching a given product image. Hong et al. (2008) presented an approach for optimally balancing various affective satisfaction dimensions based on the multiple response surfaces methodology with a case study on mobile phone designs. Shieh and Yang (2008) used fuzzy support vector machines to help product designers in a case study on mobile phone design. Yang and Shieh (2010) recommended a machine learning approach known as support vector regression (SVR) to develop a model that predicts customers' affective responses for product form design. Yang (2011a) presented a classification based on KE for modeling customers' affective responses and analyzing product form features in a systematic situation. Chan et al. (2011) proposed an intelligent fuzzy regression method generating models which represent fuzzy relationship between affective responses and design variables. Yang (2011b) integrated the methodologies of SVR and multi-objective GA into the scheme of hybrid kansei engineering system (KES). A case study of mobile phone design was given to demonstrate the analysis results. Wang (2011) proposed a hybrid KES, combining grey system theory and SVR, for effectively and accurately predicting the relationship between product form elements and product images. Oztekin et al. (2013) suggested a Taguchi based method in KE with a case study on mobile phones. From the literature, it is seen that there are many works on the affective design of mobile phones since it is accepted as a status symbol and fashion icon by customers.

The key factor in affective engineering is to transform customers' emotions on products into the design features which should be easily understood by designers. One of the efficient ways to present affective responses of customers is "if-then" rules. However, "if-then" rules might fail to represent affective responses of customers in some situations where more complex natural language based sentences are required. In this paper, we propose linguistic summarization with FS for representing customer's emotions on products using more complex statements instead of "if-then" rules. The rest of the paper is organized as follows. In section 2, basic definitions of linguistic summarization with FS are introduced. Section 3 presents the application of linguistic summarization with FS to a case study on mobile phone design. Finally, the conclusion remarks and future directions are discussed in section 4.

2. LINGUISTIC SUMMARIZATION

One of the descriptive techniques in data mining is summarization intending to discover patterns that cover overall aspect of data in a concise manner. Although the simplest form of summarization is based on the statistical methods, understanding the results obtained by them are sometimes beyond the capacities of human beings, and usually providing a limited knowledge to use. Hence, linguistic summarization with FS that generates natural language statements from data has received a great attention in the literature. The first studies on linguistic summarization using FS was proposed by Yager (1982; 1991, 1995; 1996). After that, the studies on linguistic summarization with FS have been reported under the different names such as fuzzy quantification (Barro, Bugarin, Carinena, & Diaz-Hermida, 2003; Miguel Delgado, Sánchez, & Miranda, 1999; M. Delgado, Sanchez, & Vila, 2000; Zadeh, 1983), semi-fuzzy quantifiers (Félix Diaz-Hermida & Bugarín, 2011; F. Diaz-Hermida, Bugarin, & Barro, 2003; F. Diaz-Hermida, Bugarin, Carinena, & Barro, 2004; F. Diaz-Hermida, Losada, Bugarin, & Barro, 2005), fuzzy association rules (Dubois, Hullermeier, & Prade, 2006; Dubois, Prade, & Sudkamp, 2005; Martin & Shen, 2009; Martin, Shen, & Majidian, 2010), fuzzy rules (Dubois & Prade, 1996; Serrurier, Dubois, Prade, & Sudkamp, 2007) and so on.

Before representing the idea of linguistic summarization, the related definitions on FSs are given. A FS on X, denoted by A, is defined as $A=\{\langle x,\mu_A(x)\rangle | x\in X\}$ where $\mu_A(x)$ is the membership grade of x. The α-cut of A is the crisp set $A_\alpha=\{x\in X | \mu_A(x)\geq\alpha\}$.

Let Y be defined as a set of objects $\mathrm{Y}=\{y_1,y_2,y_3,\ldots,y_M\}$, V be defined as a set of attributes $\mathrm{V}=\{v_1,v_2,v_3,\ldots,v_K\}$ and X_k $(k=1,2,\ldots,K)$ be the domain of v_k. Then $v_k^m \equiv v_k(y_m)\in \mathrm{X}_k$ is the value of the k^{th} attribute for the m^{th} objects. Most of the linguistic summarization studies have employed two summary forms based on the fuzzy quantifiers, proposed by Zadeh (1983). The first summary form called as type-I fuzzy quantified sentence is in the form of "$Q\,\mathrm{Y}'s\ are/have\ S\,[T]$". Here, Q is the linguistic quantifier labelled with FS (e.g. about half, most, etc.), Y is the set of objects, S is the summarizer labelled with FS, and T is the degree of truth describing how much data support the summary. The second summary form called as type-II fuzzy quantified sentence is in the form of "$Q\,\mathrm{Y}\ being\ w_g\ are/have\ S\,[T]$". w_g is a qualifier (pre-defined summarizer) labelled with FS. "Most tall people are blonde" can be given as an example for type-II fuzzy quantified sentences. Here, "most" is the linguistic quantifier (Q), "people" is the set of objects (Y), "tall" is the qualifier (S_g), and "blonde" is the summarizer (S). Since a type-II fuzzy quantified sentence is a general case of the type-I fuzzy quantified sentence, in this paper, we hereafter only concentrate on type-II fuzzy quantified sentences.

The degree of truth defined by Delgado et al. (2000) is used for evaluating type-II fuzzy linguistic summaries as follows:

$$T=\sum_{\alpha_i\in\Gamma(S|w_g)}(\alpha_i-\alpha_{i+1})\times\mu_Q\left(\frac{|\,S(v_S^m)_{\alpha_i}\cap w_g(v_g^m)_{\alpha_i}\,|}{|\,w_g(v_g^m)_{\alpha_i}\,|}\right) \tag{1}$$

In Eq.(1) $\Gamma(S\,|\,w_g)=\{\alpha_1,\alpha_2,\ldots,\alpha_n\}$ is a set of union of α levels of $\Gamma(S\cap w_g)\cup\Gamma(w_g)$ and it holds $0=\alpha_{n+1}<\alpha_n<\ldots<\alpha_2<\alpha_1=1$. w_g should be normal FS. If it is not normal FS, it should be normalized. $S\cap w_g$ should also be normalized by the same factor used in the normalization.

The linguistic summaries are usually evaluated by the degree of truth. But, some authors advocate that the degree of truth is solely insufficient to evaluate the quality of a linguistic summary. Therefore, we have used some additional quality measures proposed by Wu and Mendel (2011). One of these quality measures is the degree of sufficient coverage T_c, presenting generality and describing whether a linguistic summary is supported by enough data. In order to compute T_c the coverage ratio should be first calculated as:

$$r=\frac{\sum_{m=1}^{M}t_m}{M} \tag{2}$$

where t_m is defined as:

$$t_m = \begin{cases} 1, & \mu_S(v_S^m) > 0 \text{ and } \mu_{w_g}(v_g^m) > 0 \\ 0, & \text{otherwise} \end{cases}$$

r is the percentage of data which fits both the qualifier and the summarizers of a linguistic summary at nonzero degrees. r can not be used directly in the evaluation since it is usually very small. Therefore, the function determined by r_1 and r_2 (r_1 and r_2 with $0 \leqslant r_1 < r_2$ are real numbers such as $r_1 = 0.02$ and $r_2 = 0.15$), maps the coverage ratio into the appropriate T_c as follows:

$$T_c = f(r) = \begin{cases} 0, & r \le r_1 \\ \dfrac{2(r - r_1)}{(r_2 - r_1)^2}, & r_1 < r < \dfrac{r_1 + r_2}{2} \\ 1 - \dfrac{2(r - r_1)}{(r_2 - r_1)^2}, & \dfrac{r_1 + r_2}{2} \le r < r_2 \\ 1, & r \ge r_2 \end{cases} \tag{3}$$

The degree of reliability (T_r) determines whether a linguistic summary provides reliable knowledge or not. It can be stated that a summary is reliable if it has high degree of truth and a sufficient coverage. T_r is defined as:

$$T_r = \min(T, T_c) \tag{4}$$

3. APPLICATION OF LINGUISTIC SUMMARIZATION TO AFFECTIVE PRODUCT DESIGN

The mobile phones are seen as a status symbol and fashion icon according to most of young and middle aged users who give more importance to the affective dimensions of a phone (Katz & Sugiyama, 2005). Therefore, it is important to grasp what the target young users really want for designers in such a competitive market. In this section, we use linguistic summarization for extracting knowledge related to customers' affective needs on mobile phones which are very popular products, especially to the young generation. For the sake of clarity, each stage of the methodology is presented in detail on this particular example.

Step 1. Identification of semantic space: An initial semantic space was formed by interviewing users, surveying magazines related to mobile phones, scanning web pages of main mobile phone trademarks, and gathering words used from marketing personnel of a phone company. In this way, a total of 113 adjectives were obtained. Following this, using a group of four experts in mobile phone design, a reduced adjective set was established. The reason for this is that a larger set decreases the reliability due to fatigue during the semantic evaluation. Finally, eleven adjective image words are specified for describing the image of a mobile phone (Table 1).

Table 1: The Image/Impression adjectives

adj_1	New fashioned	adj_7	Attractiveness
adj_2	Sportive	adj_8	Harmoniousness
adj_3	Cheap	adj_9	Contentedness
adj_4	Simple	adj_{10}	Rigidity
adj_5	Elegance	adj_{11}	Granularity
adj_6	Luxuriousness		

Stage 2: Morphological analysis: Form elements were extracted from 73 mobile phones. As a result of morphological analysis and by referring to previous studies (Akay & Kurt, 2009; Lai et al., 2005) seven design parameters are determined from phones samples, together with their associated types (Table 2).

Table 2: Form elements

DP_1- Body shape	Parallel Line- PL	 Convex- RC	 Concave- CC
DP_2- Phone color	Plain- D	Complex- K	Patterned- DL
DP_3- Length			
DP_4- Width			
DP_5 - Thickness			
DP_6- Display dimension			
DP_7- Weight			

Stage 3: Evaluating product image of phones samples: 73 mobile phones were evaluated by 132 volunteer university students (76 male and 56 female, average age of 22). The existing literature (Dahan & Srinivasan, 2000) indicates that high-resolution photos can be used to elicit responses about products and yield results comparable to those using physical products. Therefore, semantic evaluation was performed using the pictures of phones. Images of mobile phone samples having equal sizes were presented to subjects in full-scale front and side views. Next, each subject was requested to evaluate each mobile phone presented in random order according to each adjective word on a 7-point semantic scale. There was no time limitation for the evaluation because assessment was carried out online in a web based system. Later on, aggregation on subjects' scores was realized by taking the mean value of each adjective word for each phone (Table 3).

Stage 4: Fuzzy rule extraction by Linguistic Summarization with Fuzzy Sets: A data set was formed by taking seven design parameters as the inputs in Table 4 and adjectives as in Table 3 outputs. The first and the second design parameters have categorical values, while other design parameters have continuous values. The relationships between design parameters and adjectives are represented by type-II fuzzy quantified sentences which provide richer knowledge comparing to “if-then” rules. FS used for labelling design parameters have been illustrated in Fig 2(a-f).

Table 3: Results of Semantic Differential Evaluation

Phone No.	Image/Impression adjectives						
	adj_1	adj_2	adj_3	…	adj_9	adj_{10}	adj_{11}
1	4.01	3.49	4.99	…	4.82	4.82	4.70
2	3.46	3.14	4.41	…	4.49	4.78	4.11
3	5.31	5.03	6.07	…	5.33	5.33	5.45
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
72	5.92	5.39	5.46	3.67	4.74	4.76	5.18
73	5.31	5.06	5.73	3.60	4.80	5.22	5.43

Table 4: Design parameters of mobile phones

Phone No.	INPUT						
	DP_1	DP_2	DP_3	DP_4	DP_5	DP_6	DP_7
1	PL	D	103	44	17	10.7	85
2	RC	K	106	47	18	7.98	76
3	PL	DL	88	42	23	12	104
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
71	RC	D	102	46	14	11	85
72	PL	DL	105	45	18	13	92
73	PL	K	109	53	20.9	16.3	120

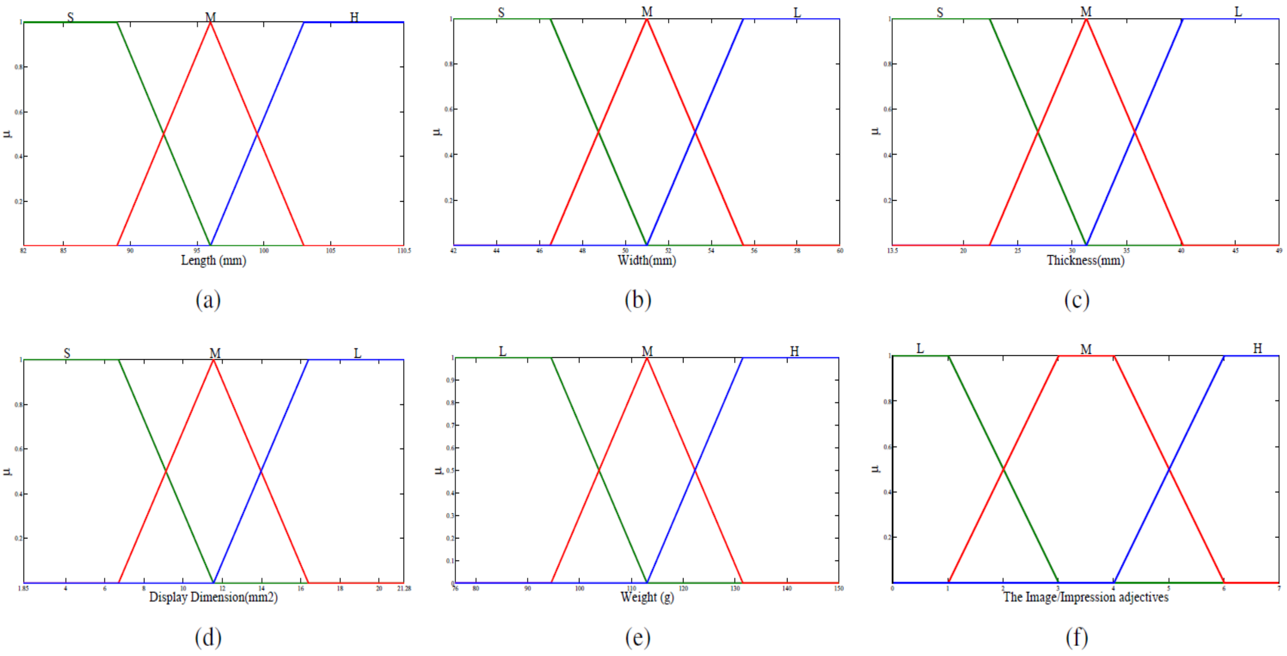

Figure 2: Fuzzy Sets for Design parameters and Adjectives (a) Length (S=Short, M=Middle, H=High), (b) Width (S=Small, M=Medium, L=Large), (c) Thickness (S=Small, M=Medium, L=Large), (d) Dimension (S=Small, M=Medium, L=Large), (e) Weight (L=Light, M=Medium, H=Heavy), (f) Adjectives (L=Low, M=Medium, H=High)

"All", "about half" and "most" have been considered as the linguistic quantifiers. The linguistic quantifiers are defined as follows:

$$Q_{All}(c)=\begin{cases}1, & c=1\\ 0, & \text{otherwise}\end{cases} \tag{5}$$

$$Q_{About\ half}(c)=\begin{cases}2c, & c<0.5\\ 2(1-c), & 1\geq c\geq 0.5\end{cases} \tag{6}$$

$$Q_{most}(c)=c \tag{7}$$

To generate, evaluate, and rank linguistic summaries, a MATLAB code has been developed. Totally, 1,621,917 linguistic summaries are evaluated by computing the degree of reliability. The top two linguistic summaries for each of the adjectives are shown in Table 5.

Table 5: The linguistic summaries obtained by computing the degree of reliability (T_r)

Adj	Rules	(T_r)
Adj_1	Most of the cell phones with high length, medium width, small thickness and light weight are medium new fashioned	0.893
	Most of the cell phones with parallel line, high length, medium width, small thickness and large display dimension are high new fashioned	0.915
Adj_2	All cell phones with high length, medium width, small thickness and medium display dimension are medium sportive	1
	Most of the cell phones with parallel line, high length, medium width, small thickness and large display dimension are high sportive	0.741
Adj_3	Most of the cell phones with high length, medium width, small thickness and light weight are medium cheap	0.866
	Most of the cell phones with high length, medium width, small thickness and large display dimension are high cheap	0.979
Adj_4	All cell phones with high length, medium width, small thickness and light weight are medium simple	0.915
	About half of the cell phones with high length, medium width, small thickness and light weight are high simple	0.420
Adj_5	All cell phones with high length, medium width, small thickness and medium display dimension are medium elegance	1
	Most of the cell phones with middle length, medium width and small thickness are high elegance	0.807
Adj_6	Most of the cell phones with high length, medium width, small thickness and light weight are medium luxuriousness	0.915
Adj_6	Most of the cell phones with high length, medium width, small thickness and large display dimension are high luxuriousness	0.936
Adj_7	Most of the cell phones with high length, medium width, small thickness and light weight are medium attractiveness	0.857
	Most of the cell phones with high length, medium width, small thickness and large display dimension are high attractiveness	0.940
Adj_8	All cell phones with high length, medium width, small thickness and light weight are medium harmoniousness	0.916
	Most of the cell phones with high length, medium width, small thickness and large display dimension are high harmoniousness	0.893
Adj_9	All cell phones with high length, medium width, small thickness and light weight are medium contentedness	0.915
	Most of the cell phones with medium length, medium width and small thickness are high contentedness	0.880
Adj_{10}	All cell phones with high length, medium width, small thickness and light weight are medium rigidity	0.916
	Most of the cell phones with high length, medium width, small thickness and large display dimension are high rigidity	0.943
Adj_{11}	All cell phones with high length, medium width, small thickness and light weight are medium granularity	0.915
	Most of the cell phones with high length, medium width, small thickness and large display dimension are high granularity	0.946

4. CONCLUSION AND FUTURE WORKS

In this paper, we have illustrated the applicability of linguistic summarization with FS to affective design for mobile phones. In the proposed approach, first, eleven adjectives have been identified to describe the image of a mobile phone. Next, 73 mobile phones have been evaluated to extract form elements, and seven design parameters have been determined from mobile phone samples. FS have been constructed for eleven adjective words and some of the design parameters. “Most”, “About half” and “All” has been considered as linguistic quantifier. The relationship between design parameters and adjective words has been presented by type-II fuzzy quantified sentences. The extracted simple and interpretable linguistic summaries have the characteristics of presenting novel ideas for successful product design. The significance of affective design is increasing more and more as the market becomes more competitive. Therefore, it is possible to use the proposed approach for other customer products such as home appliances, automobiles, furniture and so on.

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