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Soliciting customer requirements for product redesign based on picture sorts and ART2 neural network

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Abstract

Design knowledge acquisition plays an extremely important role in new product conceptualization and product redesign. This study aims at facilitating the effectiveness of product redesign activities. It involves two interrelated phases, namely customer requirements elicitation and customer requirements evaluation. Sorting techniques, picture sorts in particular, have been employed for customer requirements acquisition during product redesign process. By applying such a systematic knowledge or requirements acquisition technique, some objectives and constraints of product redesign can then be identified. Furthermore, it has become an imperative to quantitatively and automatically analyze the elicited customer requirements so as to simplify and optimize the subsequent product conceptualization and selection of conceptual design alternatives. For this purpose, the adaptive resonance theory, especially ART2, neural network has been utilized for the preliminary design decisions, such as customer segmentation, in terms of customer requirements evaluation. A case study on the mobile hand phone redesign is used to demonstrate and validate this approach.

Keywords: Product redesign; Customer requirements acquisition; Customer requirements evaluation; Picture sorts; ART2 neural network

1. Introduction

Much Research has been conducted on product information recovery from sources such as existing products for either new product conceptualization or product redesign. On the basis of the repertory and reuse of existing product information, various design strategies have been postulated and investigated, including reverse engineering (Rekoff, 1985), knowledge-based design (Mitri, 1991), evolutionary design (Qiu, Fok, Chen, & Xu, 2002) and case-based reasoning (Belecheanu, Pawar, Barson, Bredehorst, & Weber, 2003). As a result, design knowledge acquisition has secured a core position in the early stage of product development. Nowadays, researchers have realized that, for a successful product, a broader information source for product development needs to be exploited. Liu and Shyu (1997) suggested that the patent database is a valuable source for identifying information such as competitors' products, technology trends, design alternatives and background information. The information affords insights to understand the deep thoughts under an actual design, e.g., the designer's intent to adopt a specific solution that cannot be found by analyzing the existing products.

Furthermore, the Internet has evolved into a major source for information acquisition in the past few years. It was highlighted by Bergeron (2001) that the lack of direct interrelationship between environmental factors and product issues could gradually be dissolved as a result of utilizing the Web technologies. Robert and Racine (2001) conducted a study on the Internet strategy, called e-strategy, to envision the future arena of product development, including such discrete components as competition

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profiles, technological evolution, and pricing and manufacturing elements. Although much broader product-related information may be attained at present, there still exist a number of obstacles in using the collected information, for instances:

- It is heavily dependent on the functional structures rather than comprehensive design knowledge in reverse engineering process.
- It is perhaps related to a large number of unlisted sources such as patent documents, which are lack of the focus or penetration to start a specific product development.
- It is usually too general and unorganized to be useful in design projects from the Internet resources.

Therefore, the design knowledge acquired for product conceptualization or redesign should concern with both breadth and depth perspectives. That is, the product-centric information and the marketing-related or customer-oriented information are of equal importance for designers to handle the design issues. Massberg (1997) suggested that customers are the core element to undertake design tasks, and can be regarded as the starting point as well as terminal point of product development. In other words, customer's needs and expectations can be specified and quantified in terms of functional requirements, followed by sorting out the preferred alternative solutions, during the early stage of product concept development. Although some research efforts (Fung, Popplewell, & Xie, 1998; Suh, 1990; Tseng & Du, 1998) have led to a new direction to deal with product conceptualization or redesign, the bottleneck is still existed in (1) applying a single method to deal with a complex knowledge or requirements acquisition problem; (2) eliciting and analyzing customer voices when lacking of expert guidance; and (3) employing a quantitative evaluation for qualitative items.

In this paper, the proposed approach aims at soliciting customer requirements for product development, especially for product redesign. Product redesign was conventionally conducted by designers and concentrated on the recovery and refinement of the functional information of products. However, in recent years, more and more design practitioners realize that customer expectations and demands can be treated as the premise and driver to effectively select and form the functional requirements for product redesign. As a result, companies will be able to offer their products closer to the markets and customers on the basis of genuine elicitation and effective evaluation of customer requirements. For this purpose, the so-called sorting techniques, picture sorts in particular, have been employed in this study for customer requirements acquisition during product redesign process. By applying such a systematic knowledge or requirements acquisition technique, some redesign objectives and constraints can be identified. Furthermore, it has become an imperative to quantitatively and automatically analyze the elicited customer requirements so as to simplify and optimize the subsequent product conceptualization and selection of conceptual design alternatives. Therein, the adaptive resonance theory, especially ART2, neural network has been utilized for the preliminary design decisions, such as customer segmentation, in terms of customer requirements evaluation. A case study on the mobile hand phone redesign is used to demonstrate and validate this approach.

2. Customer requirements elicitation using picture sorts

2.1. Background

To ride on the paradigm shift in product development, the human behaviour and performance were studied and directed towards the human limits and differences, such as the performance measures, physiological indices and subjective responses. Nevertheless, it still remains problematic to effectively transfer physiological or psychological findings into the domain of product design or redesign. To tackle this problem, Sanders and McCormick (1987) postulated two aspects in handling the 'human criteria', viz., (1) the appreciation of design implications from customers based on the recognition of individual differences in human capabilities and limitations; and (2) the use of customer data from human behaviour to test proposed hypotheses and applied techniques. To date, the customer-oriented approach has acted as a simplification of the direct studies on human behaviour and performance in the fields of physiology or psychology. It may be based on such conceptions as physiological factor (e.g., the long-term and inherent demographic characteristics of individual customers, such as age or gender), psychological perspective (e.g., the customer perceptions and attitudes towards a company and its products), and technological consideration (e.g., a close collaboration and a logic transfer between widely-adopted knowledge acquisition techniques and the rising requirements acquisition applications).

Appropriate elicitation techniques that are able to offer a compromised solution between the extensiveness of the expertise and the genuineness of the voice of customers are necessary for effective customer requirements elicitation and evaluation. To avail the appropriate techniques to deal with a particular design task, Maiden and Rugg (1996) proposed a framework called acquisition of requirements (ACRE) to assist elicitors in identifying the feasibility of the methods, such as interview, ethnographic, sorting or laddering, for requirements acquisition. Accordingly, sorting technique that assumes customers know their needs and are able to group them into different categories presents a logical alternative. It provides a novel way for transforming physiological, psychological and technological factors into useful inputs for redesign issues.

Basically, sorting techniques are derived from Kelly's personal construct theory (Kelly, 1955) and have been applied and improved for product conceptualization with increasing frequency in recent years (Chen, Khoo, & Yan, 2005; Chen

& Occeña, 1999; Yan, Chen, & Khoo, 2002; Yan, Pritchard, Chen, & Khoo, 2006). The basic notions of sorting techniques involve a process, where objects such as pictures and cards are sorted into groups by customers. As summarized by Rugg and McGeorge (1997), sorting techniques are multi-functional, flexible, easy to use and systematic. In general, sorting techniques can be classified into four broad categories, namely Q-sorts, hierarchical sorts, "all in one" sorts, and repeated single-criterion sorts. In this work, the technique of repeated single-criterion sorts (Rugg, Corbridge, Major, Burton, & Shadbolt, 1992) has been adopted as it is more flexible and is easier for most novice elicitors to handle. Using such a technique, the same pictures are repeatedly sorted each time when a different single attribute or a sorting criterion is used. More specifically, picture sorts that enable novice respondents to detect the slight difference between sorted pictures, and thereafter extract the cause for that effect, have been chosen to elicit customer requirements.

2.2. Picture sorts

Picture sorts for customer requirements elicitation comprise five main steps, namely selecting the entities, preparing the pictures and instructions, conducting the session, recording the session, and analyzing the criteria and categories (Rugg & McGeorge, 1999). Table 1 shows the definitions of terminology used in sorting techniques. For clarity, these five main steps are briefly described as follows:

Step 1. *Selecting the entities.* The basic principle regarding the choice of entities involves two aspects, namely appropriate semantic coverage and appropriate level of hierarchy. The number of entities is recommended to be more than eight.

Step 2. *Preparing the pictures and instructions.* Pictures should conform to the same standards, that is, the same size, the same background and the similar glossiness. In addition, they need to be randomly numbered and free of extraneous features. An explanation of the picture sorting process for all the respondents to follow is desirable.

Step 3. *Conducting the session.* Once the pictures and instructions are available to the respondents, a sorting session is activated. During which the respondents should sort pictures into groups, with one group for each category, using only one criterion or requirement in each sort, that is, repeated single-criterion sorts. Upon completion, the respondents verbalize their constructs and name the categories. They must also ensure that there is no leftover, that is, no item not belonging to any of the groups. The dyadic (or triadic) elicitation technique is further used to elicit more constructs from explicit knowledge to semi-tacit or tacit knowledge of some kinds, if necessary.

Step 4. *Recording the session.* To avoid mistakes in recording a session and to save recording time, it is advisable to use code numbers instead of meaningful names.

Step 5. *Analyzing the criteria/categories.* The analysis of the recording from a session generally depends on the purpose of the session. This includes the number of criteria, the type of criteria, the commonality of criteria, the distribution of commonality and the analysis of categories.

2.3. Specifying picture sorts for customer requirements elicitation

In the event of using picture sorts for customer requirements elicitation during product redesign, it is more likely to select a set of existing design alternatives belonging to one sub-tree of a specific product as entities to formulate sorted pictures. For example, the pictures of these existing design alternatives can be chosen from a series of product pictures or computer-aided design (CAD) drawings. Basically, the number of criteria provides an indication about the range of knowledge within the population of respondents. As for the commonality of criteria (i.e., the tastes or different cultures of respondents), it indicates the amount of overlap between respondents. As for analysis of categories, it is fairly similar to those for criteria. It includes the number of categories, the type of categories,

Table 1
Definitions of terminology used in sorting techniques

Terminology	Definition	Example
Construct	An attribute used by an individual to describe something	Light weight
Superordinate construct	The attribute grouped from the criteria in a higher abstraction level	Use new material to reduce weight
Imposed construct	The high-level attribute abstracted from the superordinate construct	Usability
Criterion	The attribute used as the basis for a sort when using a sorting technique, also called 'verbatim construct'	Light weight is preferred
Category	A group into which things may be classified, using a criterion, also called 'subordinate construct'	Plastics, composite materials
Entity	The objects selected for formulating pictures in picture sorts	A series of design solutions
Design alternative	A concept or solution in one sub-tree of a specific product	Light-weighted type

the commonality of categories and the distribution of categories within a criterion.

To facilitate and simplify customer requirements solicitation for product redesign, the statistical results obtained from the picture sorts need to be treated, which involves (1) grouping the verbatim constructs into the superordinate constructs and (2) defining the imposed constructs by domain experts. Here, the technique of picture sorts is used as a toolkit in order to derive the customer attributes hierarchy (CAH) (Fig. 1), viz., a customer-explored architecture. The CAH is a generic taxonomy, which is set up by a domain expert according to the significance of the results of performing sorting technique on the customer voices. Amongst this taxonomy, verbatim construct stands for the voice of customers, and the imposed constructs will then be graded to generate the importance ratings as the inputs to the ART2 neural network described in Section 3.

The approach comprises two sessions of sorting process as shown in Fig. 1, where the importance ratings from customers are applied in the second session by the same groups of the respondents. Basically, sorting techniques, particularly picture sorts, depend much on the way in which the sorting process is designed, conducted and controlled by the elicitors. Undisputedly, the respondents play an important role in defining the initial groupings for customer requirements elicitation. It is apparent that collaborative efforts of elicitors, respondents and experts are needed during the phase of repeated single-criterion sorts. In product redesign, a further customer requirements evaluation phase is critically needed to elicit the customer expectations or demands amongst diverse customer groups via customer segmentation depicted in Section 3. Consequently, it can be expected that, if the distribution of commonality between the customer groups is sparse, different patterns such as different tastes or colours for a redesigned product will then be considered. In this way, picture sorts provide a means to pre-process the complex customer voices into useful information. Upon completion of the picture sorts, the input samples from the customer importance ratings for the imposed constructs are processed by a neural network classification engine presented in Section 3.

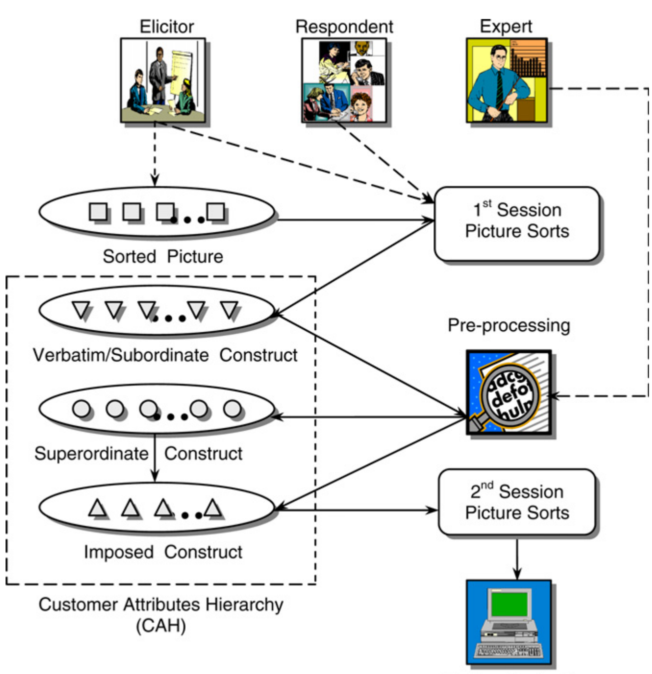

Fig. 1. Procedure of specified picture sorts for product redesign.

3. Customer requirements evaluation using ART2 neural network

3.1. Related work

Customer requirements elicited from one customer group may have considerable conflict with another, based on such demographic characteristics as age or gender. Hence, the variation must be considered during the early stage of product development. On the other hand, the qualitative inherence of voice of customers usually contains ambiguity and subjectivity with overlaps and conflicts, whereas picture sorts alone are poor at handling concepts that are fuzzy and have no clear-cut boundary between sets of objectives. As such, it is imperative to detect customer requirements from different customer groups, and thereafter, analyze these requirements and bridge customer's demands with the products of a company. For this purpose, a neural network approach to map the customer information obtained from picture sorts into customer patterns is proposed in this study.

It has been proven that neural network is one of the most effective artificial intelligence (AI) technique for multi-disciplinary applications, of which business-based or marketing-related strategy is becoming a popular domain. Amongst these approaches, the feed-forward neural networks, such as radial basis function (RBF) network (Yan, Chen, & Khoo, 2001), have frequently been employed in terms of marketing segmentation or forecasting. On the other hand, the self-organized neural network, such as Kohonen self-organizing map (SOM) algorithm (Chen, Khoo, & Yan, 2006), has increasingly been accepted as a cluster analysis toolkit in this area. In this study, the adaptive resonance theory, particularly ART2, neural network algorithm (Carpenter & Grossberg, 1987) is adopted owing to:

1. Similar to other neural network strategies, it can plastically adapt to such complex (often uncertain or inconsistent) and correlated (non-linear and not isolated) situations in market analysis rather than those linear functions such as *K*-means clustering model (Nilson, 1995).
2. Contrast to the supervised neural networks, it possesses faster incremental learning ability without requiring

large samples as well as self-organized inherence without any predetermined targets or desired outputs (Haykin, 1999).
3. Compared with the SOM algorithm, it can deal with pattern recognition more flexibly and independently due to automatic detection of output patterns (Principe, Euliano, & Lefebevre, 2000).

3.2. Algorithm of the ART2 neural network

The customer importance ratings to imposed constructs (an $n \times k$ matrix with n-dimensional ratings and k-dimensional respondents) are used as the inputs to the ART2 network for automated customer clustering of output patterns. The ART2 is an unsupervised neural network with an adaptive resonance theory (ART) architecture for performing both continuous-valued vectors or binary-valued vectors. A typical ART2 architecture was first proposed by Carpenter and Grossberg (1987) as illustrated in Fig. 2 (only one unit of each type is shown here).

In the attentional sub-system, an input pattern $\boldsymbol{s}$ is first presented to the F_1 layer, which consists of six kinds of units viz. the W, X, U, V, P and Q cells. It then undergoes a process of activation, including normalization, noise suppression and updating. This results in an output pattern $\boldsymbol{p}$ from the F_1 layer. Responding to this output pattern, an activation is produced across F_2 layer through bottom-up weights b_{ij}. As the F_2 layer is a competitive layer with a winner-talk-all mode, only one stored pattern is a winner. It also represents the best matching pattern for the input pattern at the F_1 layer. Furthermore, the pattern of activation on the F_2 layer brings about an output pattern that is sent back to the F_1 layer via top-down weights t_{ji}.

For the orienting sub-system, it contains a reset mechanism R and a vigilance parameter ρ to check for the similarity between the output pattern from the F_2 layer and the original input pattern from the F_1 layer. If both patterns are concordant, the neural network enters a resonant state where the adaptation of the stored pattern is conducted. Otherwise, the neural network will assign an uncommitted (inhibitory) node on the F_2 layer for this input pattern, and thereafter, learn and transform it into a new stored pattern. The training algorithm can be described as the following steps:

Step 1. Initialize parameters of a, b, c, d, e, θ, α and ρ, where a, b are the fixed weights in the F_1 layer, c is the fixed weights used in testing for reset, d is the activation of winning F_2 unit (also satisfies $cd/(1-d) \leqslant 1$), e is a small parameter to prevent division by zero when the norm of a vector is zero, θ is the noise suppression parameter (generally $\theta \cong 1/n^{1/2}$), α is the learning rate, and ρ is the vigilance parameter (usually $0.7 \leqslant \rho < 1$). Then, randomly select an input vector $\boldsymbol{s}$ and repeat from Step 2 to Step 6.

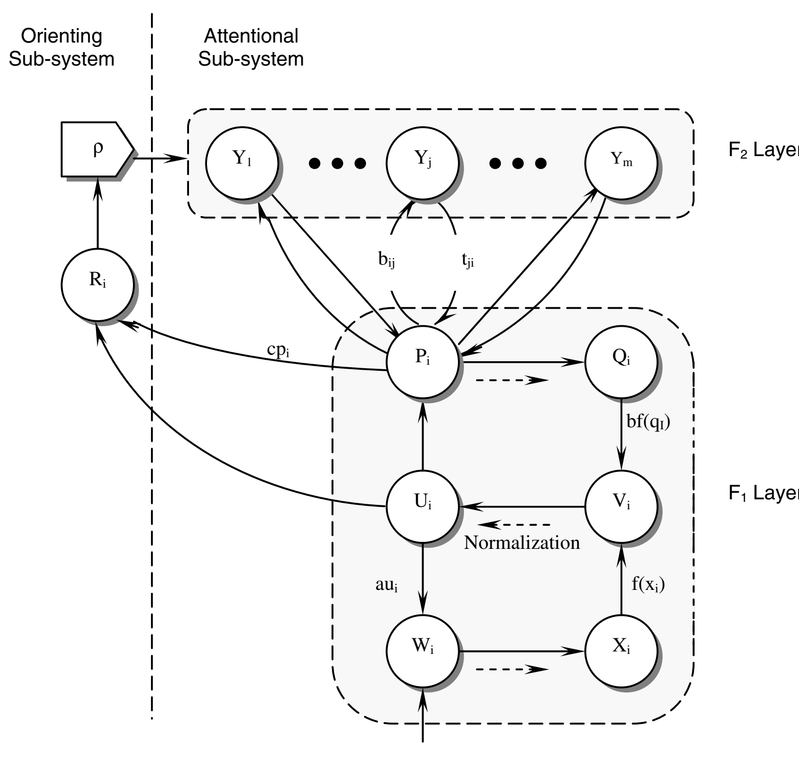

Fig. 2. Typical architecture of ART2 neural network.

Step 2. Update F_1 unit activation using Eqs. (1)–(7). Initially, let $u_i = 0$, $p_i = 0$ and $q_i = 0$ (where the number of input patterns $i = 1, 2, \ldots, n$), thereafter, update F_1 unit activation again.

$$u_i = \frac{v_i}{e + \|\mathrm{v}\|} \tag{1}$$

$$w_i = s_i + au_i \tag{2}$$

$$p_i = u_i \tag{3}$$

$$x_i = \frac{w_i}{e + \|\boldsymbol{w}\|} \tag{4}$$

$$q_i = \frac{p_i}{e + \|\boldsymbol{p}\|} \tag{5}$$

$$v_i = f(x_i) + bf(q_i) \tag{6}$$

where the activation function is

$$f(x) = \begin{cases} x & \text{if } x \geqslant \theta \\ 0 & \text{if } x < \theta \end{cases} \tag{7}$$

Step 3. Compute signals to F_2units, and find Y_J with the largest signal (assumed that $y_J \geqslant y_j$, for $j = 1, 2, \ldots, m$, where m is the number of output patterns).

$$y_j = \sum_i b_{ij} p_i \tag{8}$$

Step 4. Check for reset by updating u_i according to Eq. (1), along with using Eqs. (9) and (10).

$$p_i = u_i + dt_{Ji} \tag{9}$$

$$r_i = \frac{u_i + cp_i}{e + \|\boldsymbol{u}\| + c\|\boldsymbol{p}\|} \tag{10}$$

If $\|\boldsymbol{r}\| \geqslant \rho - e$, then update other F_1 units according to Eqs. (2), (4)–(6), and continue the following steps. Otherwise, return to Step 3 for finding the second largest signal and check again. If no pattern concords, this uncommitted node on the F_2 layer will be learnt and transformed as a new stored pattern.

Step 5. Update weights of the winning unit J for a certain iterations until the weight changes are below some specified tolerance. Consequently, update F_1 activations according to Eqs. (1), (2), (4)–(6) and (9):

$$t_{Ji} = \alpha du_i + (1 + \alpha d(d-1))t_{Ji} \tag{11}$$

$$b_{iJ} = \alpha du_i + (1 + \alpha d(d-1))b_{iJ} \tag{12}$$

Step 6. Test the stopping condition for weight updates and for number of epochs involved. For example, repeat Steps 2–6 until the placement of output patterns does not change from one epoch to the next.

3.3. Specifying the ART2 neural network for customer requirements evaluation

To acquire customer requirements, imposed constructs are first elicited via the multi-level architecture obtained from the sorting process. Next, the customer importance ratings with respect to imposed constructs are formed as the inputs to an intelligent engine for automated customer segmentation. In this work, the ART2 neural network approach is employed to group the information obtained from picture sorts into patterns regarding different customer groups. On the basis of customer segmentation, marketing analysis can be performed for further customer requirements evaluation. As such, the results obtained from the ART2 network need to be further analyzed:

(i) *Customer segmentation*. The output patterns from the ART2 network are automatically formed based on the customer importance ratings of imposed constructs, i.e., the number of output pattern is identical to that of output cluster. In addition, the cumulative number of respondents in relation to each output pattern can be used as the criterion for subsequent marketing analysis.

(ii) *Marketing analysis*. Marketing analysis comprises major customer group identification, competition analysis and customer trends forecast. Firstly, the ART2 network outputs are organized according to multi-cultural customer groups such as age, gender and skill. Subsequently, major customer groups are identified from the output patterns that contain majority of respondents (or customers). Competition analysis is then conducted by comparing the output patterns with the number of respondents in those patterns from the surveying company and those from its main competitor. The customer trends forecast is then performed based on the output patterns as well as the number of respondents in those patterns.

4. A case study on mobile hand phone design

This case study involved the redesign of a mobile hand phone, and was based on the assumption that the respondents possess some knowledge about mobile hand phones. Nine pictures of existing design alternatives were used in this study (a sample picture and the instructions for picture sorts are provided in Appendix A). The pictures of these design alternatives were chosen from a series of computer-aided design (CAD) drawings, which were randomly numbered at their right upper corner. Each picture was standardized in terms of size, quality and glossiness. Twelve (12) respondents were chosen for the sake of customer attributes hierarchy (CAH) elicitation via picture sorts. Subsequently, the ART2 network was employed for clustering customer patterns. The multi-cultural customer groups (100 respondents) were first chosen and discriminated according to gender, age and education.

The respondents were composed of two categories of different gender, namely male and female respondents. Each category consisted of 50 respondents. Half of the respondents were younger than 35 and another half were older than 35. Furthermore, half of them belonged to the high-educated respondents and the others belonged to the low-educated respondents. In the first session of picture sorts, the respondents elicited their own criteria/categories (verbatim/subordinate constructs) using repeated single-criterion sorts. Subsequently, the superordinate constructs were pre-processed. After that, the domain expert was then asked to define a set of imposed constructs. In the second session of picture sorts, customer importance ratings were collected.

After the CAH has been established, the customer importance ratings from '0.1' to '1.0' (0.1 stands for least important and 1.0 stands for most important) to imposed constructs were completed. In the same manner, three sets of customer data (100 respondents each) from customer ratings towards imposed construct were then used for the analysis of major customer groups, competition and customer trends analysis, residing in the aforementioned customer requirements evaluation process. For examples, customer data from the surveying company versus its main competitor are used for competition analysis, and past and present customer data are used for customer trends analysis. Fig. 3 presents the CAH derived from the sorting process for the redesign of a mobile hand phone. A multi-level structure was obtained, together with six (6) imposed constructs, sixteen (16) superordinate constructs and forty-two (42) verbatim constructs. It was observed that a large number of verbatim, superordinate and imposed constructs elicited possessed overlapped (high-commonality of distribution) facets. For example, Imposed Constructs 'Basic requirements' and 'Standard design' are largely shared by basic demands for ease of part manufacture or change. On the other hand, conflicts (adverse correlation) between imposed constructs such as the low price from 'Basic requirements' versus the additional 'life-style' function of 'Excited features' can also be detected.

In this work, the ART2 network was employed after the respondents completed the importance ratings to each imposed construct. The graded imposed constructs were then organized into a feature matrix and used as inputs to the ART2 network for learning and customer group clustering. For instance, if six (6) imposed constructs are graded by one hundred (100) respondents, an input matrix of 6×100 dimensions will form the input samples. The

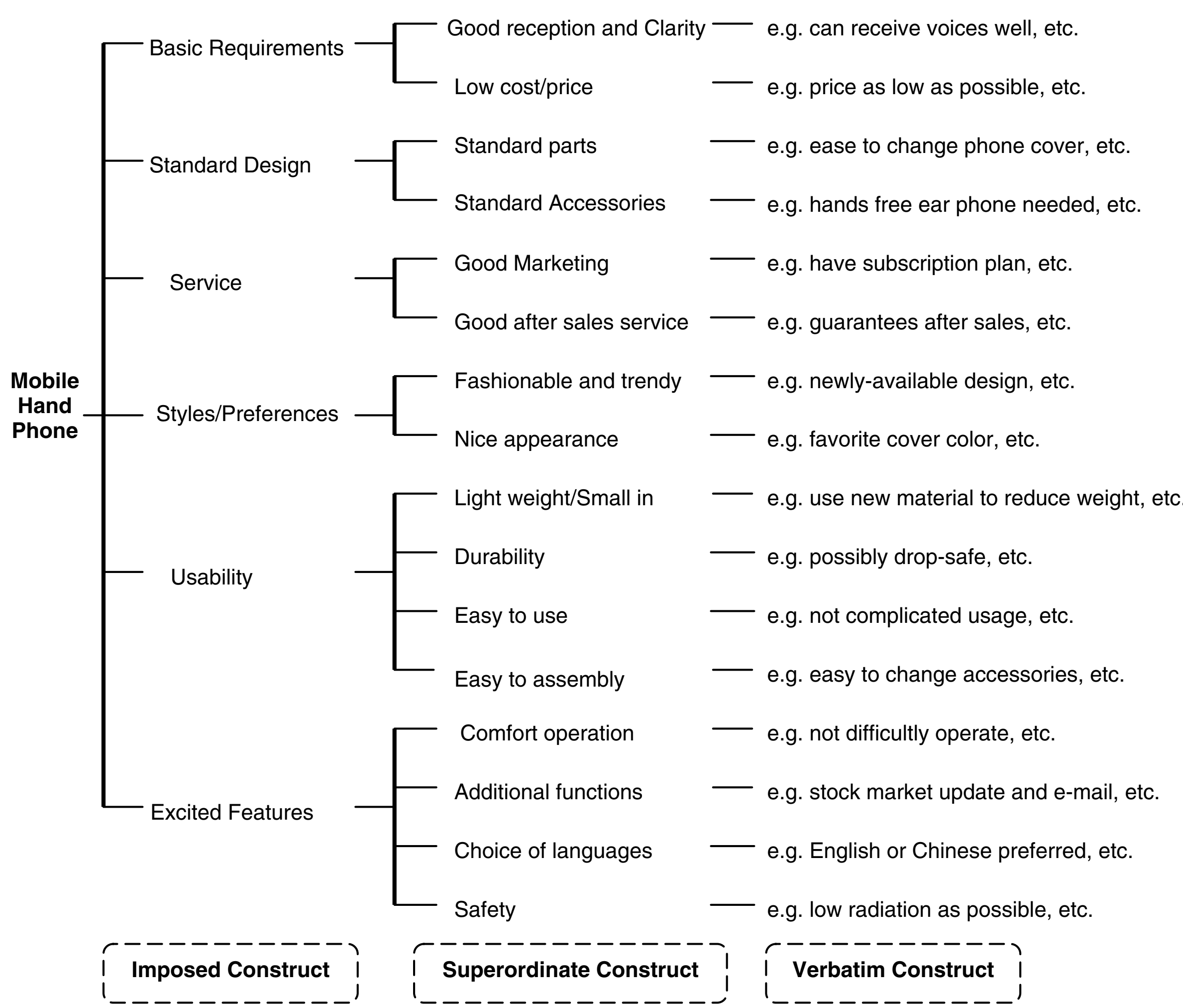

Fig. 3. Customer attributes hierarchy derived from the sorting process.

network's output is the pattern for customer group clusters, as explained in Section 3. Table 2 lists the initialized specifications of the ART2 network. Fig. 4 illustrates the training results of weight changes of a sample input vector.

Table 3 presents the ART2 network output results, which are organized according to multi-cultural customer groups such as age, gender and education. As shown in Table 3, five diversities (from Pattern 1 to Pattern 5) are identified, in which Patterns 2 and 3 are the major customer groups with 33 and 41 out of 100 respondents, respectively. From Fig. 5(a) and Table 3, it can be observed that:

- The network output of Pattern 2 is activated by female respondents rather than male respondents, as well as by the low-educated respondents rather than the high-educated respondents.

Table 2
Initialized specifications of the ART2 neural network

Initial specification	Value
Fixed weights, a	10
Fixed weights, b	10
Reset weights, c	0.1
Winning unit activation, d	0.9
Small-valued parameter, e	0
Noise suppression parameter, θ	0.4
Learning rate, α	0.3
Vigilance parameter, ρ	0.7
Initially, $u_i = 0$, $p_i = 0$, $q_i = 0$, $t_{ji} = 0$, $b_{ij} \neq 0$	

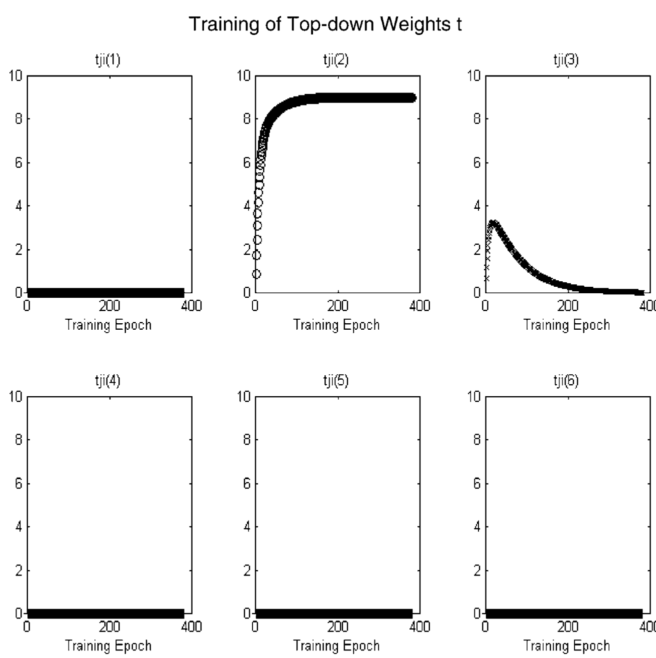

Fig. 4. An example of weight changes in the ART2 network training process.

Table 3
Results from the ART2 network regarding present data of the surveying company

Multicultural customer group		Output pattern					Sum
		1	2	3	4	5	
Age	<35	1	17	30	0	2	50
	⩾35	13	16	11	5	5	50
Gender	Male	10	10	26	4	0	50
	Female	4	23	15	1	7	50
Education	Low-educated	4	23	22	0	1	50
	High-educated	10	10	19	5	6	50
Sum per group		14	33	41	5	7	100

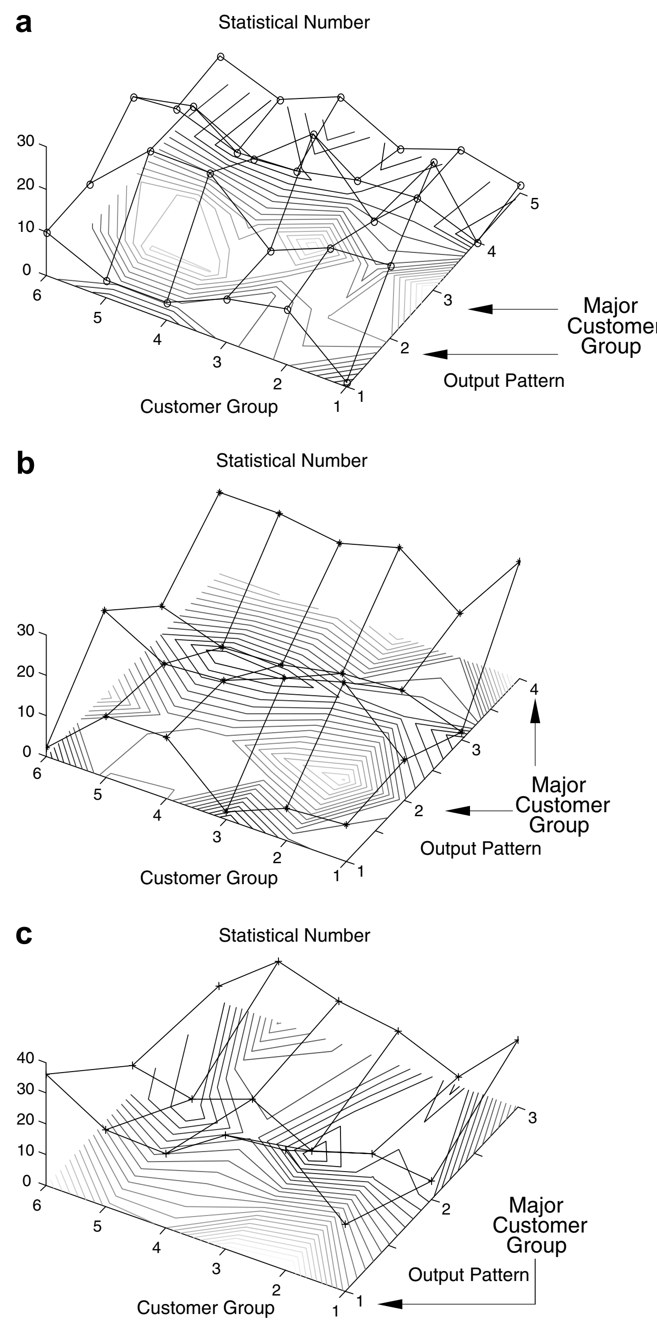

Fig. 5. Representation of statistical respondent number from the ART2 network: (a) present customer data of the surveying company, (b) present customer data of main competitor, and (c) past customer data of the surveying company.

- The network output of Pattern 3 is mainly formed by the younger male respondents, where almost equivalent number of the low-educated respondents and high-educated respondents is detected.
- The network output of Pattern 1 possesses the medium statistical number of respondents, it implies that those male respondents older than 35 are usually the high-educated respondents.
- The network output of Patterns 4 and 5 can be regarded as minor customer groups with relatively small number of respondents.

By the same token, Tables 4 and 5 list the results obtained from the ART2 neural network, which will be used for competition analysis and customer trends analysis, respectively. More specifically, the competition analysis can be conducted by comparing the results from the surveying company, shown in Table 3, and those from its main competitor, shown in Table 4 and Fig. 5(b). Likewise, the customer trends analysis can also be proceeded on the basis of the results from the present customer data (Table 3) and those from the past customer data as shown in Table 5 and Fig. 5(c).

According to Tables 3 and 4, quite similar customer and marketing orientations are detected between the surveying company and its main competitor. However, different customer orientations can still be identified between them as follows:

- Two major customer groups of the high-educated male respondents older than 35 (Patterns 2 and 3 in Table 4) were found from the main competitor. It implied that the surveying company is behind its main competitor upon this customer orientation.
- Two major customer groups of the female respondents (Patterns 2 and 5 in Table 3) were identified from the surveying company, which revealed that the surveying company possessed an advantage on this customer orientation against its main competitor.
- A major customer group of the younger respondents was detected from both the surveying company and its main competitor (Pattern 3 in Table 3 and Pattern 4 in Table 4), respectively. Therefore, the customer orientation of this customer group could be treated as a competitive opportunity for both companies as no company was judged to be superior in this direction.

Table 4
Results from the ART2 network regarding present data of main competitor

Multicultural customer group		Output pattern				Sum
		1	2	3	4	
Age	<35	9	10	2	29	50
	⩾35	8	24	7	11	50
Gender	Male	2	20	6	22	50
	Female	15	14	3	18	50
Education	Low-educated	15	13	2	20	50
	High-educated	2	21	7	20	50
Sum per group		17	34	9	40	100

Table 5
Results from the ART2 network regarding past data of the surveying company

Multicultural customer group		Output pattern			Sum
		1	3	3	
Age	<35	22	6	22	50
	⩾35	39	8	3	50
Gender	Male	37	2	11	50
	Female	24	12	14	50
Education	Low-educated	25	5	20	50
	High-educated	36	9	5	50
Sum per group		61	14	25	100

Refer to Tables 3 and 5, it can be observed that

- Fewer customer orientations as well as major customer groups were existed previously, which means fewer product concepts or design alternatives were demanded by customers in the past than at present; and
- In the context of the major customer groups, the customer orientation has shifted from the high-educated male respondents older than 35 (Pattern 1 in Table 5 and Fig. 5(c)) in the past to female and younger respondents at present (Patterns 2 and 3 in Table 3 and Fig. 5(a)).

5. Concluding remarks

It is highly desirable to establish a systematic approach for customer and marketing analysis as the initial or fundamental investigation prior to product redesign. For this purpose, a process that concerns with the breadth and depth of customer requirements solicitation has been proposed and illustrated in this study. The proposed approach, which concentrates on the integration of marketing perspectives and redesign issues, comprises two interrelated phases, namely the customer requirements elicitation phase and the customer requirements evaluation phase. Basically, it synthesizes the customer involvement and marketing analysis for product redesign. As a result, the proposed approach possesses the following strengths.

- The picture sorts can systematically elicit the customer requirements and then organize them using the so-called CAH for further analysis.
- The ART2 neural network can effectively evaluate the multi-cultural factors during customer and marketing analysis.

A case study on mobile hand phone design was used to illustrate the performance of the proposed approach. In the case study, the sorting technique, particularly picture sort, has demonstrated its effectiveness in eliciting customer requirements in product redesign. The ART2 neural network that requires simple input matrices of graded imposed constructs provides an efficient means to analyze competition and customer trends statistically. It is envisaged that with the genuine voice of customers as well as the competition and customer trends identified, more reasonable new concepts for product redesign can be gleaned. As a result, organizations can gain a competitive edge in product development.

Appendix A. Picture sample and instruction for picture sorts

A.1. Example of the sorted picture

See Fig. A.1.

A.2. Instructions of picture sorts

A total of nine pictures (numbered on the top from #1 to #9), which denote design alternatives during mobile hand phone redesign, are given for sorting. You are asked to sort the pictures into groups, using one criterion at a time until out of criteria. Note that the criterion for each sort, as well as the relevant groups containing code numbers of pictures are recommended to be written down for later recording. Any criteria and groups can be used. Following is an example of recording a sort (see Fig. A.2).

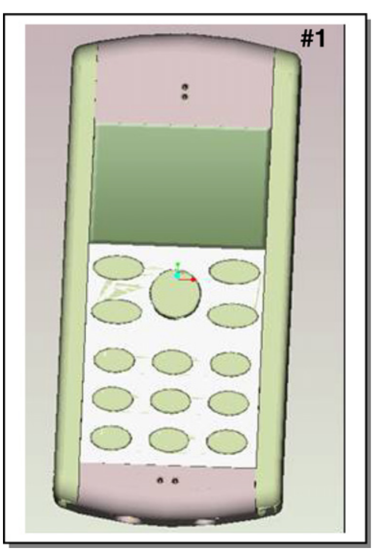

Fig. A.1. A sample picture for picture sorts.

Sort Number: 1			
Criterion: Price			
Categories:	Low	Medium	High
Picture Number:	1,3,7,9	2,6,8	4,5

Fig. A.2. Example of sorting records.

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