INTERNATIONAL DESIGN CONFERENCE - DESIGN 2010
Dubrovnik - Croatia, May 17 - 20, 2010.

UNDERSTANDING THE NATURE OF DEEP IMPRESSIONS BY ANALYZING THE STRUCTURE OF VIRTUAL IMPRESSION NETWORKS

M. Y. N. Fasiha, Y. Sakayama, E. Yamamoto, T. Taura and Y. Nagai

Keywords: deep impressions, human preference, structure of impressions, latent impressions, virtual impression network

1. Introduction

UCD (User Centered Design) is one major topic in the design research field. The long history of UCD has roots in the investigation of the human factors and focuses on human experience (EX) of a product. Actually, according to a survey of UCD practitioners, customer satisfaction is pointed out as the most important measure of UCD effectiveness [Vredenburg, 2002]. Nowadays, the user's cognitive interpretation of the designed product has been focused on as an essential factor for customer satisfaction. As [Norman, 2004] highlights, the interaction between affect, emotion, and cognition, the human behavioural emotional response to a product design is a major attribute for a product's success. This study assumes that there is some kind of emotional 'impression', which the user attains from the product and is expected to affect the user's behaviour (for example, buying behaviour). The final goal of this study is to develop a method to support designers to create products that are congruent with the users' emotional feelings, that is, products that are preferred by many people. In this paper, we propose a method to evaluate user's emotional impressions that may be essential for designing 'truly good' products that resonate with the deep feelings of human beings. We believe that the essential nature of users' impressions is related to these underlying deep feelings that may exist underneath the *surface impressions* that a user ordinarily holds when looking at a product. In this study, we focus on *deep impressions*, which are defined as the impressions that are related to the deep feelings towards a product and lie under the surface impressions. Obtaining an understanding of deep impressions is expected to capture the nature of preference that an individual may have with regard to a product. This will also give the designers practical hints for designing better products since the user's true preference for a product cannot be evaluated by surface impressions. In this study, we focus on the difference between the feelings of 'like' and 'dislike', since 'like' and 'dislike' are fundamental emotions on products and understanding its nature is necessary for emotional design. We assume that the feeling of 'like' is essentially different from that of 'dislike' at a deep impression level. In order to approach the above issue, we try to propose a method for capturing deep impressions.

1.1 Surface and deep impressions

Several methods have been proposed in order to enable the designer to understand the user's impressions, the most general one being the Semantic Differential (SD) Method [Osgood, et al., 1957]. This method has been applied to several products in various fields. It focuses on quantitatively measuring a user's impression of products and solving the difficulty of expressing the user's impression of a designed product by using words and scales provided in the answer form. However, in this method, it is necessary to decide upon the evaluation items beforehand. The items involve pairs of antonymic adjectives or nouns, for example, bright and dark, and the scales range from 1 to 5 or 7. In addition, in order to explain the obtained result, the evaluation data are finally interpreted by humans. Additionally, the SD method is a method of persistently measuring the difference in the impressions that some products had on individuals, and the results cannot be evaluated without the products or the people that were compared. This seems to present a surface analysis of the impression and we call the impression analyzed through this method a 'surface impression'. Although some methods are proposed on the basis of fuzzy theories such as rough sets [Pawlak, 1982], which are expected to overcome these problems, it seems difficult to capture deeper impressions.

On the other hand, we believe that 'like' and 'dislike' impressions are essentially different, that is, they cannot be measured on the same scale. Despite measuring the impressions on a scale, for example, when the individual rates the product closer to 'bright' or 'dark', we believe that the process that occurs when people have 'like' or 'dislike' impressions of an object are essentially different. In other words, while 'dark' implies 'almost not bright', 'dislike' is assumed not to imply 'almost not like'. We believe that the notion of deep impressions is closely related to this difference.

1.2 Preferences and deep impressions

Researchers in psychology have discussed the idea of feelings or preferences with regard to whether they require extensive cognitive processing. A widely-argued paper [Zajonc, 1980] specifically suggested that affect (responses of liking or disliking a stimulus) is so fundamental to an organism that it should be nonconscious and must occur without cognition. Of course, some form of recognition must have occurred, but it must be primitive or minimal, although not at a conscious level. The conditioning of affective responses is known as Evaluative Conditioning (EC). A study examined the role of awareness in EC and suggested that awareness is in no way influenced by EC [Baeyens, et al., 1990]; however, the results are still refutable since the evidences are unequivocal. We believe that there may exist certain 'deep factors' that work with affect processing and result in the development of preferences. In this study, we attempt to construct a methodology for capturing deep impressions. Specifically, we attempt to capture the nature of human preference, which is not possible by analyzing surface impressions.

2. Viewpoint of this study

In order to capture deep impressions, we focus on the notions of 'structure of impression' and 'latent impression'.

2.1 Structure of impressions

Aristotle said, 'The whole is more than the sum of its parts'. This concept is well-known in various sciences for its complexity and is called 'holism'. There exists 'something' that appears as a whole. In an attempt to capture the 'something', we focus on constructing the structure based on each impression and assume that the structure can play the role of the whole impression that leads to deep impressions.

2.2 Latent impressions

We believe that human beings cannot express all their impressions explicitly. Some studies have discussed this matter and have referred to the notion of 'latency'. Latent sensitivities are on the rise in many fields of design. As an example, Dong proposed a latent semantic approach to studying design team communication [Dong 2005]. These researches indicate that latent sensitivities can be used to extract relations that cannot be expressed explicitly.

These studies indicate that the notion of latent impressions may be related to deep impressions.

3. Purpose and method

The purpose of this study is to construct a methodology in order to capture deep impressions. In order to accomplish this, we propose a method for constructing 'virtual impression networks', which involves the notions of 'structure' and 'latency', using a semantic network.

3.1 Virtual impression network construction

In order to construct a virtual impression network, we use words that express the impressions held by a user who is required to describe his/her impressions of a product using certain words. We call the words 'explicit impression words'. A semantic network (explained in the next section) is used to trace a virtual chain of nodes (representing the meaning of words), that is, the path from an explicit impression word to another. We assume the nodes that appear in the paths to be the latent impressions. We construct a network in which the searched paths are considered a representation of a virtual impression network. Thus, a virtual impression network consists of two types of nodes—explicit impressions and latent impressions. We extract the structure of the virtual impression network and analyze it using the network theory, which is expected to involve the notion of the 'structure' of impressions.

Figure 1 shows the construction of the virtual impression network. This modeling method consists of the following three steps:

- Step 1: Tracing paths between every two explicit impression words (first diagram in Figure 1).
- Here, a node represents the meaning of a word, and a path is a set of direct links joining two
- word meanings. The words expressing the meanings that are found along each path are
- regarded as latent impression words.
- Step 2: Drawing a network with the explicit and latent impression words as nodes and the links
- as the extracted paths (second diagram in Figure 1).
- Step 3: Extracting the structure of a virtual impression network (third diagram in Figure 1).

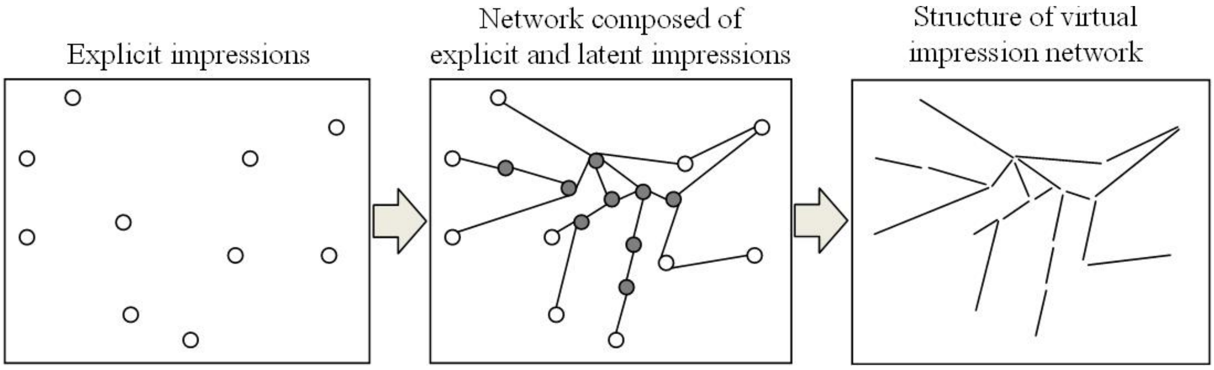


Figure 1. Flow of modeling

3.2 Semantic network

Recently, some studies in the design domain have used semantic networks. Semantic networks have structures composed of the semantic relations between words, such as the hypernym-hyponym relation and associated relations. In actual practice, semantic networks are useful in searching for links between words. To be precise, semantic networks can be used to search for virtual chain processes between two words.

As described in Section 2.1, a design methodology was proposed on the basis of the significance of the relatedness or similarity between the paths of two concepts by employing the lexical database, WordNet, as a semantic network and by measuring the relatedness or similarity with the concept evaluation tool within its database [Georgiev, et al., 2008]. In order to obtain a better understanding of the nature of design creativity, a virtual thinking network has been constructed using a semantic network, and the structure of the virtual thinking network is found to correlate with the evaluated creativity of the actual design idea [Yamamoto, et al., 2009]. In this study, we believe that they are suitable for the virtual modeling of the impressions.

Figure 2 shows an image of how one would search for a path between two words in a semantic network. The circles represent nodes in the semantic network. The white circles are nodes of explicit impression words and the black ones are nodes of impression words appearing on the path between the nodes of the explicit impression words, and the arrows are the links comprising the paths.

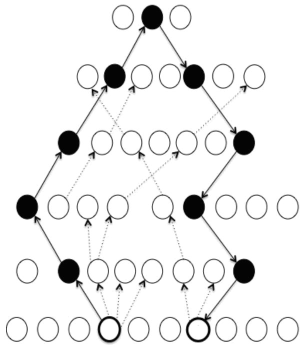


Figure 2. Image of searching for a path between explicit impression words

Semantic networks have word meanings as nodes. Therefore, we tried to trace the shortest path for any pair of the meanings of the explicit impression words and extracted the latent impression words in the path between the explicit impression words. The number of links was used as the length criterion for the paths. We obtained only one shortest path for each pair. When a pair had two or more shortest length of paths, we selected the path involving the most popular word meanings on the semantic network as the shortest path.

3.3 Structure analysis

Using the network theory, we analyze the structure of the virtual impression network in order to find an effective pattern for the deep impressions. We prepare a graph consisting of a set of *nodes* and a set of *links* joining the nodes. Although a wide range of statistical criteria exist in the network theory, in this study, we use a few important criteria to characterize the virtual impression network. We chose the same network statistical criteria as those in the study of Steyvers and Tennenbaum [Steyvers and Tennenbaum, 2005]. They used the criteria to examine whether semantic networks have a structure that is necessarily different from that of other complex natural networks. Since we are using a semantic network and the network of the user's impressions is part of a complex natural network, we decided to use the same criteria.

On the basis of the assumptions stated below, we applied these criteria to extract the nature of deep impressions.

- n, <k>, and Density can indicate the expansion of the impressions.
- C, L, and D can indicate the complexity of the impressions.

The extension of the impressions is thought to be related to deep impressions since the product that resonates with deep feelings is expected to induce the user to associate them with many impressions. On the other hand, human knowledge is like a complex network composed of pieces of knowledge and the relationship between each piece and its complexity appears in an individual's feeling space. Therefore, we believe that the complexity of a virtual impression network can be considered as a clue to extract the nature of deep impressions.

Table 1 summarizes the definitions of the network theory criteria used in this study. The number of nodes n denotes the number of nodes, which are expressed as words, appearing in each network. The number of links that are joined to a node is called *degree*, and the average degree $<k>$ is the average number of links joining a node in the network.

Two joined nodes are said to be *neighbours*. The probability that the neighbours of an arbitrary node are each other's neighbours is defined by the clustering coefficient C. In terms of network topology, a high probability signifies the existence of 'shortcuts' or 'triangles' in the network. The presence of shortcuts or triangles is common in complex networks. In other words, C indicates the complexity of the network. Figure 3 is an illustration of the calculation of C in this study. We calculate C by taking the average of C_i:

$$C_i = T_i \bigg/ \binom{k_i}{2} = 2T_i / k_i(k_i - 1) \qquad (1)$$

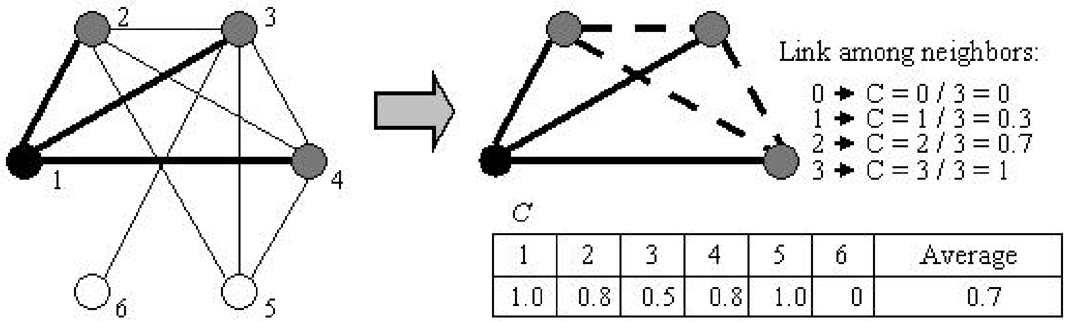


Figure 3. Example of the calculation of the clustering coefficient

where T_i denotes the number of links between the neighbours of node i, and $k_i(k_i - 1)/2$ denotes the number of links that would be expected between the neighbours of node i if they formed a fully joined subgraph. The character L denotes the average number of links of the shortest (or geodesic) paths between every pair of nodes over the entire network, and D denotes the longest path in the set of shortest paths.

The *Density* of a network indicates the sparseness of the network and is calculated by dividing $<k>$ by size n of the network; thus, the network has a high sparseness when the *Density* is low.

Table 1. Definitions of terms in network theory

Term	Definition
n	Number of nodes
<k>	Average degree (degree = number of links)
C	Clustering coefficient
L	Average length of the shortest path between every pair of nodes
D	Diameter of the network (the longest path among the shortest paths)
Density	Sparseness of the network (the percentage of how a node is joined to other nodes)

4. Experiment

An experiment was conducted in this study. In the experiment, the subjects were asked to perform two kinds of tasks. One was to describe their impression by using certain words by looking at a picture of each product. Another was to indicate the boundary of 'like' and 'dislike' for the products. All the subjects were Japanese. Ten adult graduate students participated in this experiment and six different cups were used for the experiment.

4.1 Method

In the first task (description of impression), the subjects were shown a picture of each cup and were asked to describe their impression of the cups using some Japanese words. The categories of nouns, adjectives, and verbs were required to be set out in separate columns with at least one word for each category. The participants were given two minutes for each cup in this task.

In the second task (indication of boundary), the subjects were asked to rank all the six cups according to their preference and draw a boundary of their likes and dislikes.

4.2 Results

Here, we show the results for one subject. The number of explicit impression words described by this subject for a cup shown in Figure 4 is 20. The impression words are shown in Table 2.

Table 2. Example of impression words given by one particular subject regarding one particular cup

Noun	Adjective	Verb
cup winter sea saucer spoon coffee black tea cake weight fall	weak usage difficult small cold blue	hold carry break cleaning

Figure 4. Picture of one particular cup that was shown to the subjects

5. Analysis

By means of the results, we examined the difference between the virtual impression networks of each subject of the products that were evaluated as ‘like’ or ‘dislike’ by the subject. In order to appropriately use the semantic network (WordNet 3.0), we first conducted two preprocesses (explained in Section 5.1). Then, we constructed a virtual impression network for each subject while looking at each product according to the network construction method explained in Section 3.1. We then visualized the networks using a network analysis tool [Pajek—Programme for large network analysis, http://vlado.fmf.uni-lj.si/pub/networks/pajek/]. The same tool was used to analyze the network structural characteristics. Finally, we categorized the virtual impression networks into two—the ‘like’ networks and the ‘dislike’ networks—and examined the difference in the structural characteristics between both categories. The ‘like’ network is the virtual impression network of each subject on the products that were evaluated as ‘like’ by the subject; the ‘dislike’ network is the virtual impression network of each subject on the products that were evaluated as ‘dislike’ by the subject.

5.1 Preprocess

WordNet 3.0 [http://wordnet.princeton.edu/] is a huge electronic lexical database that contains information on the manner in which human beings process language and concepts. Currently, the database comprises over 150,000 words. Words are organized in hierarchies and are interconnected by various semantic relations such as synonyms, hypernyms-hyponyms, and meronyms. The advantage of using WordNet as a semantic network is that it is practically useful for finding links between words.
In order to appropriately use WordNet, we conducted two preprocesses. Since the WordNet database is developed in English, we initially translated the impression words collected from the experiment (in Japanese) into English. In this process, we thoroughly confirmed that the meanings were consistent with the original meanings. Further, in WordNet, links are presented only between words belonging to the same POS (part of speech; for example, noun-noun). Thus, to enable the search for links between words, we replaced all the verbs and adjectives with their corresponding nouns.

5.2 Analysis of the structure of virtual impression network

We constructed virtual impression networks for each subject. In total, 60 virtual impression networks were constructed—34 were 'like' and 26 were 'dislike' virtual impression networks. We extracted the structural characteristics of the networks using the criteria listed in Table 1 and examined the structural differences of virtual impression networks between both the categories.

As a result, we found significant differences in two of the criteria—the average degree <*k*> and clustering coefficient *C*. Graphs depicting the differences of means for all the network criteria are shown in Figure 5.

We found that the average of average degree <*k*> of 'like' virtual impression networks is significantly higher ($t(58) = 2.037$, $p < 0.05$) than those of the 'dislike' networks. This suggests that <*k*> can indicate significant facts that many explicit and/or latent impressions are associated when the product resonates with the user's deep feelings. In other words, the <*k*> can show the expansion of explicit and latent impressions; impressions are expanded when a user looks at a 'truly good' product.

We also found that the average of clustering coefficient *C* of the 'like' virtual impression networks is significantly higher ($t(58) = 2.262$, $p < 0.05$) compared to the average of those of the 'dislike' networks. This shows that *C* can indicate the complexity of the explicit and/or latent impressions. The significant difference implies that the complexity of the explicit and/or latent impressions may also be the essence that differentiates human preference.

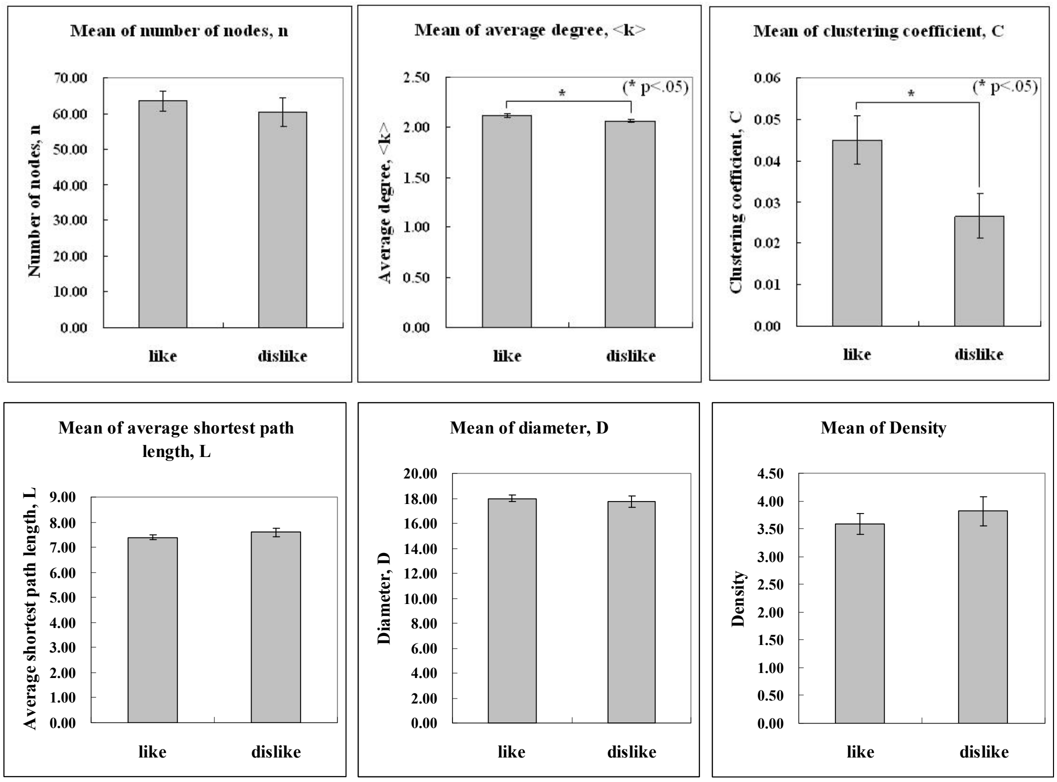
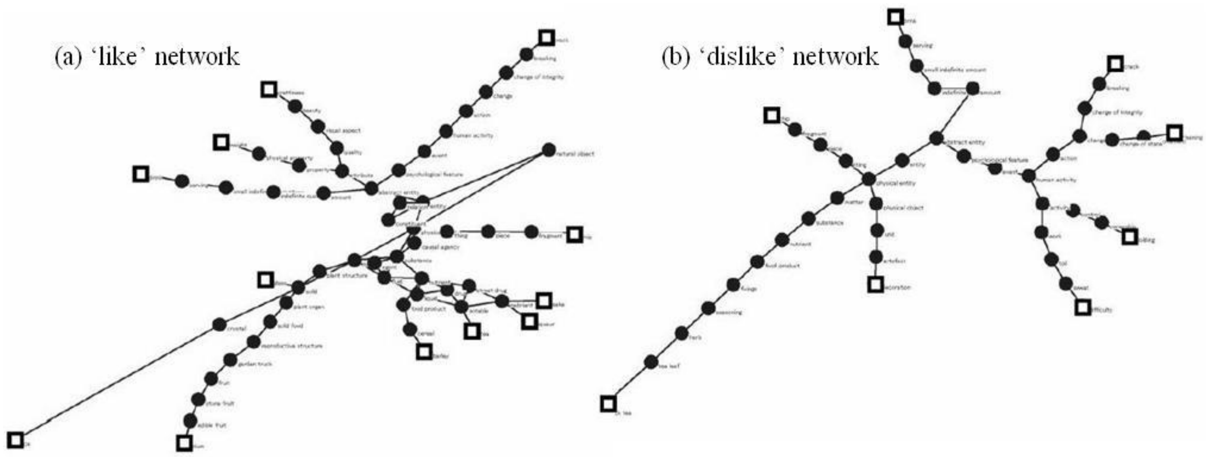


Figure 5. Means of the values of network criteria

Figure 6 shows examples of virtual impression networks drawn using Pajek and their corresponding network term values. Both networks virtually represent the impressions of one person—(a) of his/her 'like' network and (b) of his/her 'dislike' network. The figure illustrates that the average number of links joined to a node is more in his/her 'like' network compared to those in his/her 'dislike' network. The expansion of the virtual impression network is demonstrated in the 'like' network. In addition, there exist many 'shortcuts' or 'triangles' (that illustrate the value of *C*) in the 'like' network; in other words, higher complexity is seen in the 'like' network.

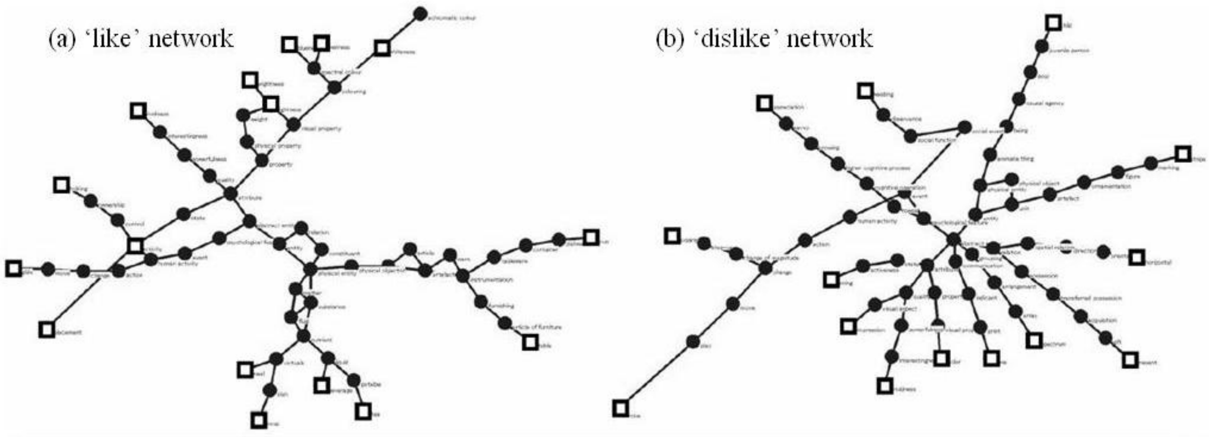
The examples of 'like' and 'dislike' networks of different persons when looking at the same cup are shown in Figure 7. Figure 7 shows (a) the virtual impression network of the person who likes the cup and (b) the virtual impression network of the person who does not like the same cup. The same tendencies as in Figure 6 are observed in the networks; there exist more links joined to a node and more 'shortcuts' or 'triangles' in the 'like' network. The examples implies that the structural difference between 'like' and 'dislike' networks are neither dependent on the people nor on the cups and suggest the applicability of our proposed method.

In addition, we observed the explicit impression words in the networks. The words in the example networks are listed in Table 3. We observed that the explicit impression words in the 'like' networks are more related to each other. For example, the words *barley*, *tea*, *liqueur*, and *sake* from the network in Figure 6 (a) are related in the group 'beverages'. These words exist near the 'triangles' in the network. In the network in Figure 7 (a), the words close to the 'triangles', namely, *meal*, *soup*, *beverage*, and *tea* come from the group 'nutrient' and *cup* and *table*, from 'instrumentation'. This implies that when people have a good impression of a product, they tend to think deeper in a certain direction. Some research findings suggested that attractive things make people feel good, which in turn expands their thought processes, thereby becoming more creative and imaginative; when people are anxious, they tend to narrow their thought processes, concentrating upon aspects directly relevant to a problem [Norman 2004]. In this study, when the subjects were not attracted to the product, they tended to concentrate on the task in order to list their impressions. Hence, the impression words are more apart. On the other hand, when they were attracted to the product, they tended to be more creative, think further in a certain direction, and expand their impression by listing more related impression words.



	n	<*k*>	*C*	*L*	*D*	*Density*
(a)	61	2.4262	0.1534	6.8853	20	3.9774%
(b)	44	1.9545	0	7.8858	19	4.4421%

Figure 6. Examples of virtual impression networks of a person: (a) is his/her 'like' network and (b) is his/her 'dislike' network. □ is the explicit impression node, and ● is the node appearing in the path between the explicit impression nodes



	n	$\langle k \rangle$	C	L	D	Density
(a)	60	2.2333	0.0822	7.2955	17	3.7222%
(b)	68	2	0	6.9899	16	2.9412%

Figure 7. Examples of virtual impression networks of two different people when looking at the same cup; (a) is a network of the person who likes the cup and (b) is a network of the person who does not like the cup. ☐ is the explicit impression node, and ● is the node appearing in the path between explicit impression nodes

Table 3. Explicit impression words in the networks in Figures 6 and 7

Figure 6		Figure 7	
(a) 'like' network	**(b) 'dislike' network**	**(a) 'like' network**	**(b) 'dislike' network**
barley	black tea	table	stroke
tea	chip	cup	expansion
liqueur	drink	whiteness	appreciation
sake	crack	redness	wedding
chip	cleaning	blueness	child
crack	holding	brightness	stripe
prettiness	difficulty	lightness	spectrum
weight	decoration	vividness	present
drink		glide	horizontal
glass		activity	line
ice		holding	colour
plum		placement	swing
		beverage	vividness
		tea	impression
		meal	
		soup	

6. Conclusion and discussion

In this paper, we attempted to capture the nature of the deep impressions that exist underneath the impression that a user has of a product. We expected that the nature of human preference of the product, which appears to be difficult to evaluate according to the surface impressions, can be understood by capturing the deep impressions. For this purpose, we proposed a method for modelling users' deep impressions using a semantic network and constructed a virtual impression network. We then quantitatively analyzed the structure of the network using the network theory. We focused on two viewpoints that are related to deep impressions—the structure of impressions and latent impressions.

We compared the structural characteristics of the virtual impression network of ‘like’ and ‘dislike’ and found significant differences in several criteria.
These findings suggest that the feeling of ‘like’ is different from that of ‘dislike’ at the deep impression level. The difference, since it appeared in the structure that plays the role of a whole impression, may be observed at the process of impressions’ initiation; the manner in which humans attain impressions, good or bad, is essentially different. These findings indicate that products should be designed so that the structure of the virtual impression network involves the ‘like’ structure, that is, a high value of $<k>$ or C. This measurement of the deep impression on the products is expected to be used to analyze the directions of the brand leader or evaluate the prototypes of the products at the early stage of the design process.
Our findings lead to the conclusion that the understanding of the deep impressions may be the clue in understanding human preference; hence, this model could be applicable for extracting clues that may be practical for designers in designing better products. In future, we will attempt to extract certain clues in order to assist the design of ‘good products’.

References

Baeyens, F., Eelen, P., Van den Bergh, O., "Contingency Awareness in Evaluative Conditioning: A Case for Unaware Affective-evaluative Learning", Cognition and Emotion, Vol.4, 1990, pp 3-18.
Dong, A., "The Latent Semantic Approach to Studying Design Team Communication", Design Studies, Vol.26, No.5., 2005, pp 445-461.
Georgiev, G. V., Taura, T., Chakrabarty, A., Nagai, Y., "Method of design through Structuring of Meanings", Proceedings of the International Design Engineering Technical Conference and Computers and Information in Engineering Conference (IDETC/CIE) – ASME (DETC2008-49500), 2008.
Norman, D. A., "Emotional Design: Why We Love (or Hate) Everyday Things", Basic Book, New York, NY, 2004.
Osgood, C. E., Suci, G. J., Tennenbaum, P. H., "The Measurement of Meaning", University of Illionis Press, Urbana, 1957.
Pawlak, Z., "Rough Sets", International Journal of Computer and Information Sciences, Vol.11, No.5., 1982, pp 341-356.
Steyvers, M., Tennenbaum, J. B., "The Large-Scale Structure of Semantic Networks: Statistical Analyses and a Model of Semantic Growth", Cognitive Science, Vol.29, 2005, pp 41-78.
Vredenburg, K., Mao, J., Smith, P. W, Carey, T., "A Survey of User-Centered Design Practice", Proceedings of CHI 2002, Minneapolis, Minnesota, Vol.4. Issue 1, 2002, pp.471-478.
Yamamoto, E., Goka, M., Yusof, N. F. M., Taura, T., Nagai, Y., "Virtual Modeling of Concept Generation Process for Understanding and Enhancing the Nature of Design Creativity", Proceedings of the 17th International Conference of Engineering Design, Stanford University, San Francisco, CA, 2009.
Zajonc, R. B., "Feeling and Thinking: Preferences Need No Inferences", American Psychologist, Vol.35, 1980, pp 151-175.

Nor Fasiha Mohd Yusof
Kobe University
Department of Mechanical Engineering
Creative Design Lab.
1-1 Rokkodai, Nada 657-8501, Kobe, Japan
Telephone: +81 78 8036151
Telefax: +81 78 8036155
Email: norfmy@stu.kobe-u.ac.jp