Modeling of Tacit Knowledge and Its Application
Case Study: Web Page Layout Design
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Abstract: A method for modeling a tacit knowledge has been developed. Tacit knowledge is a type of knowledge that is difficult to describe with words or symbols such as sports techniques, design skills, etc. It is difficult for us to obtain and share this type of knowledge. In this paper, we discuss a new method to create a model of tacit knowledge by showing an example of web site designing. Usually, capable designers can express their intentions precisely through their works. This is to say, appearances of their works reflect their intention. Thus, it is expected that capable designers’ tacit knowledge can be extracted from their works. Knowledge of the design was extracted from actual web pages on the Internet. Then, knowledge models were created by utilizing a Bayesian network. The created models were verified by LOOCV technique. The result shows that one of the created models illustrates part of a designers’ knowledge accurately.

Keywords: Tacit knowledge, Bayesian network, Correlation analysis

1. INTRODUCTION

Nowadays, many companies encounter strong global competition, so they have to increase their competence. Knowledge sharing is one crucial factor for organizations to survive intense competition [1]. It has also been pointed out that knowledge sharing practices in an organization are very important for facilitating innovation and improving performance [2]. Thus, knowledge sharing should be prioritized in organization activities.

Tacit knowledge is a significant chapter of the knowledge theories. It can be described as personal knowledge and difficult to formalize. This type of knowledge is acquired through experience, observation and imitation, and it cannot be transmitted easily with language [3]. Thus, this type of knowledge is difficult for us to obtain and share. Here, if tacit knowledge can be visualized as a model, it becomes easy to comprehend. A visual designing process is a good example that requires tacit knowledge. Usually, the client expects the result of designing to look a certain way. Capable designers can easily create appropriate designs that reflect clients’ requirements but this is not simple for novice designers. Thus, to create an effective design, the creator has to implement his/her intended impressions in the correct form. Then, the users can feel the intended impression from the artifact. This scheme can be represented as an analogy of the communication process model proposed by Shannon and Weaver [4]. The transmission processes of general information and a design image are shown in Figure 1 (a) and (b), respectively.

For successful communication, a sender must transmit information to a receiver precisely. In a communication system, the sender encodes a message into codes that consist of a series of symbols based on their own inherent knowledge. The symbols may be written or spoken words, pictures, music, etc. The symbols reach the receiver via a channel. Then the code is decoded, and the receiver can understand the information. In this process, the information channel is influenced by several noises and the noises may distort the original information. Usually, many digital communication channels have mechanisms to reduce the effects of noises. Meanwhile, in the transmission process of a design image, such a noise reduction system cannot be put between designer and user. Thus, the design process is more difficult than the encoding process in verbal communication, so a support system is required.

This study employs a layout design process for web pages as an example. Other elements such as colors, pictures, etc. were ignored because we already have many theories that deal with impressions of them. An experiment was conducted to investigate how the collected web pages reflect the images. Then, models of design knowledge were created by using Bayesian network theory. These knowledge models can restrict the amount of noise in the communication system. Moreover, the knowledge model may help inexperienced designers to conveniently create a web page at an expert level.
2. RELATED STUDIES AND BACKGROUND THEORY

This paper discusses a way to visualize tacit knowledge of visual design. Relationship between layout items and the impression of visual design are illustrated by using Bayesian network models. In this section, two types of knowledge, tacit knowledge and explicit knowledge, are referred in order to discuss the knowledge related to visual design.

Explicit knowledge is objective information that can be described logically by using words or formulas. Generally, this type of information can be transmitted and shared easily [5]. On the other hand, tacit knowledge is subjective knowledge that can be obtained through training or personal experience and is difficult to describe in term of procedures or rules. Thus, these types of knowledge are difficult for us to transmit and share [6]. Several studies have been conducted to visualize tacit knowledge. The SECI (Socialization, Externalization, Combination, and Internalization) model represents the process of creating new knowledge and sharing it through transition between tacit and explicit knowledge. Through the transition process, tacit and explicit knowledge expand in terms of both quality and quantity [7]. Figure 2 illustrates the SECI model. There are four steps of knowledge conversion. The first step is Socialization in which person’s tacit knowledge is shared to create public tacit knowledge. The Externalization step describes how tacit knowledge is articulated in an explicit form. During the Combination step, the explicit knowledge is systematized. The last step is Internalization in which the new tacit knowledge is crystallized [8]. The SECI model clarifies procedures to share tacit knowledge clearly. The knowledge sharing among individuals in an organization is required fundamentally to achieve innovation and organizational success. It also promotes the creation of values within a company [9, 10].

Igarashi et al. [11] proposed a tacit knowledge model based on cello performances. They focused on the differences in bow movement between novice and expert

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**Figure 1**: Schemata of communication showing how general information and design image are transmitted and processed

**Figure 2**: Model for creating organization knowledge: SECI model
cellists. The Bayesian network was adopted to visualize the sequential movement of each joint of a finger. The difference between beginners and experts was clarified by comparing the structures of models. This study was done to support improvements in cello performance. This research aimed to visualize the knowledge of the playing skills, which is another example of implicit knowledge.

Knowledge used in a design process can also be considered as tacit knowledge. Of course, some such knowledge can be regarded as explicit knowledge. For instance, some kinds of knowledge of design can be represented by rules and definitions, such as natural language or symbols, called “design language [12]” in design education. However, general design skills can be called a type of tacit knowledge. To communicate intended impressions of designers to the users precisely, some researchers have proposed methods to develop design laws that represent the relationship between user’s impressions and design appearance. For example, Sakamoto et al. [13] investigated the relationship between impressions of colorations and operations in a design of touch panel devices. They found that usability, accuracy, and amenity of operations can be improved by considering the differences in brightness among colorations used for the touch panel interface. Moreover, Sato et al. [14] evaluated impressions using the Semantic Differential (SD) method on web pages. The correlation between design of web pages and impression words was examined, and an impression scale was generated. They revealed that the design of web pages affects a user’s impression. Nevertheless, they did not specify which elements affect impression.

Consequently, in this paper, the authors aim to illustrate the elements of design that affect a user’s impression.

3. RESEARCH METHODOLOGY AND RESULTS

The relationship between impression and layout items of a web page is investigated. Then, the associated models are created by using a Bayesian network to visualize the tacit knowledge.

Since outcomes of expert designers should reflect their intentions, the relationship between design and the intention should be clarified. To obtain an expert’s design knowledge, we assume that web pages, created by capable designers contain the designers’ intentions. Such intentions are especially reflected in the elements of the web pages such as font style, font size, text margin, etc.

The outline of the proposed method is shown in Figure 3. The first step is selecting impression words that represent designers’ intentions and collecting representative web pages of the impressions. Then, the layout information is extracted from these web pages. Subsequently, the relationship between impressions and layout items is investigated and verified through experiments. Afterward, the knowledge models of the web page’s layout design are created. The optimal model is chosen to be the representative model. In this section, the details of the method are explained with an example of creating a web designing knowledge model.

3.1 Select impressions

The first step is selecting impressions that explain a designer’s intention. The Japanese Color and Design Research Institute developed a cluster of impressions called the language image scale [15], which has two axes: the Warm-Cool axis and the Soft-Hard axis. Nearly 180 adjectives are located on the scale. Each word expresses an impression associated with a color. The space represented by the language image scale can be divided equally to nine domains as shown in Figure 4:
Warm, Cool, Soft, Hard, Warm-Soft, Warm-Hard, Cool-Soft, Cool-Hard, and Neutral. In this paper, these nine keywords are used for representing impressions of web sites.

3.2 Obtaining layout items

The second step is collecting layout items. Ninety web pages were selected from the Internet. Each web page reflects an impression that corresponds to a position on the language image scale.

The data of layout items were extracted from contents of the ninety web pages. Usually, a web page is constructed by using many layout elements such as letter characteristic, text margins, color schemes of the image, etc. To focus on the relationship between the impressions and layout items, color scheme of the web page and image data were ignored.

Generally, contents on web page are marked up with HTML. Meanwhile, elements of a web page, layout, colors, and fonts are defined with a CSS (Cascading Style Sheet). A CSS file is embedded into an HTML document, and it defines the layout of the page.

A content of a page can be divided into three domains, as mentioned in Table 1. The layout elements used in this paper are defined in Table 2.

Many web pages are used for advertising products or providing services. Usually, the impression of a web page depends on the category of such products and services. For example, the website that advertises soft drinks should provide a cool image, and a page providing a financial service should have a hard image. Thus, the genres of products and services can be classified in accordance with the expected impression. Therefore, genre can be employed as a criterion for classifying web sites that represent each impression. Eighty-five web pages were selected to be the sample web pages. Brainstorming was conducted to class product genres by considering the impressions. The product genres were arranged on the language image scale as shown in Table 3.

Table 2: The Definition of layout elements and example of CSS code which are used in the paper

| Layout element | Definition | Example of CSS code |
|---------------|------------|---------------------|
| Font family   | The style of the letters. Fonts can be classified into two font families: Japanese and Latin. The Japanese font family includes Gothic, Ming, and Cursive styles. Meanwhile, the Latin font family includes Sans-Serif and Serif styles. | h1 {font-family: serif} |
| Font size     | The size of the letters that is a vertical measurement from the reference base line. | h1 {font-size:12px} |
| Font weight   | The weight or the boldness of the letters. | h1 {font-weight:400} |
| Line height   | The distance between the base line and the next adjacent line. | h1 {line-height:21px} |
| Letter spacing| The distance between the regions of adjacent letters. | h1 {letter-spacing:3px} |
| Margin        | The space between the text boxes. | h1 {margin-top:20px; margin-bottom:20px; margin-right:20px; margin-left:20px;} |
| Padding       | The distance from the box frame to the letter domain in the box. | h1 {padding-top:15px; padding-bottom:15px; padding-right:15px; padding-left:15px;} |

Table 3: Genres that represent each impression

| Impression   | Typical product genre |
|--------------|-----------------------|
| Warm         | Ethnic foods          |
| Warm-Soft    | Baby items            |
| Soft         | Weddings              |
| Cool-Soft    | Mineral water         |
| Cool         | Fashionable apparel   |
| Cool-Hard    | Government administration office |
| Hard         | Brand suits           |
| Warm-Hard    | Japanese traditional festivals |
| Neutral      | City hotels           |
3.3 Investigate relationship between impressions and layout items

The third step is investigating the relationship between impressions and layout items. The web pages that reflect the nine impressions mentioned above were collected from the Internet. Ten pages for each category, i.e., the ninety web pages, were obtained. The data was analyzed by ANOVA and statistically analyzed.

ANOVA was conducted to investigate the differences layout information between each product genre. The following six items are significantly different in each genre \((p < 0.05)\): Title-Text size, Title-Font weight, Body-Text size, Body-Line height, Body-Letter spacing, and Body-Left margin. The following four items show a marginally significant difference in each genre \((0.05 \leq p < 0.1)\): Title-Letter spacing, Title-Left padding, Subtitle-Font weight, and Subtitle-Line height. In the results, the mean values of these layout items were different in each product genre.

3.4 Verify correlation between impressions and layout items

The fourth step is conducting an experiment to verify if the layout information extracted from the collected web pages reflects the expected images correctly. The outline of the method for creating web pages that are used in the verification step is shown in Figure 5. Two web pages are selected from the samples for each impression. Eighteen web pages are obtained in this way. The CSS files were extracted from the selected web pages. Then, 18 test pages are created with a test HTML file and 18 extracted CSS files.

Twenty participants took part in this experiment (four participants were students from a design department of university). The Thurston’s comparison was used to verify the image of the sample pages. In this procedure, the participants were shown a pair of pages, and asked to compare the pages on the basis of their impressions, and this was repeated until all combinations had been shown. First, participants were asked which page was harder on the hard-soft scale. After all web pages were judged, the same procedure was conducted again on the warm-cool scale. Participants judged all web pages using two images scales (hard-soft and warm-cool images). Figures 6 and 7 show the results on the hard-soft and warm-cool scales, respectively.

From Figure 6, we can see that many web pages categorized into soft groups are located on the soft side. Meanwhile, from Figure 7, we can see that some web pages categorized into cool group are located on the cool side. This means that the soft-cool axis is trustworthy.

3.5 Create model of design knowledge

The last step is generated the models that represent the relationship between two impressions (soft and cool images) of page and the layout items. The Bayesian Network is used to structure the models. Then, the suitable model is distinguished by using the leave-one-out cross validation (LOOCV) method.

Usually, input data of Bayesian network should be discrete values. Discretization of the layout items was performed because the raw data obtained in the previous steps were continuous values. Then, the associated models were structured by using Bayesian network techniques. The data analysis software “R” was utilized for generating the models.

![Figure 5](image)

**Figure 5:** Procedure of making sample pages for the experiment
Four models were created with the algorithms listed in Table 4. These models are shown in Figures 8, 9, 10, and 11.

From the model structures, we can notice that there are six nodes that involve two impression nodes (soft and cool images). As a result, the eight crucial nodes were assessed in order to evaluate the accuracy of models:

- Two impressions (cool and soft) shown in yellow circles
- Three layout items that closely correlated with cool and soft impressions (title-font weight, subtitle-font weight, and body-padding-top) shown in red circles
- Three layout items that connected with the cool and the soft impressions (title-font family, body-font size, and body-margin-left) shown in blue circles

The LOOCV was adopted to assess how well models perform. The results show that the ratios of correct answers of model 4 are higher than the chance levels for seven nodes as well as being the best for all models overall. Therefore, the model 4 represents knowledge of web designers best in these models. The fitness was also

Table 4: Structure learning algorithm and network scores in each model

| Model   | Structure learning algorithms | Network scores                      |
|---------|-------------------------------|-------------------------------------|
| Model 1 | Hill Climbing                 | Akaike’s information criteria (AIC) |
| Model 2 | Hill Climbing                 | K2 evaluation value                 |
| Model 3 | Tabu Search                   | Akaike’s information criteria (AIC) |
| Model 4 | Tabu Search                   | K2 evaluation value                 |
evaluated by using four information criteria tools: AIC, BIC, Log-likelihood, and K2. As a result, we can see that model 4 is the most suitable model to visualize the knowledge of the layout design. The results of evaluation are shown in Table 5.

4. DISCUSSION AND CONCLUSION

This paper discussed a method for visualizing of tacit knowledge. Designing skills for web sites were especially focused on. The correlation between layout items and impressions was investigated and represented as knowledge models, which were created by using Bayesian networks. Four models were created by combining two kinds of structure learning algorithms and two kinds of network scores methods. From the results, the model created with the K2 evaluation level and the Tabu search algorithm was the most appropriate. However, concerning the attributes of cool and soft, the ratios of correct answers are quite low. This indicates that this model is not suitable to estimate impressions of cool and soft. On the other hand, this knowledge model may be superior to estimate style of font and text size because the percentage of correct answers is rather high.

The models created with the proposed method could be used for developing a design support system for web pages, which would work like an expert system. Such a system would be beneficial for inexperienced designers because they could receive useful advice from the system just like from expert designers. In addition, this system would infer the duplication of expert knowledge. From this function, the implicit knowledge could be transmitted to and shared with the public. Moreover, organization intellect in the field of design would be developed by utilizing our methodology.

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