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ORIGINAL ARTICLE

Graphical Modeling Method of Texture-related Affective and Perceptual Responses

Kensuke KIDOMA*, Shogo OKAMOTO*, Hikaru NAGANO** and Yoji YAMADA*

** Nagoya University, Nagoya-shi, Aichi 464-8601, Japan*
*** Tohoku University, Sendai-shi, Miyagi 980-8577, Japan*

Abstract: Techniques for modeling hierarchical and multidimensional human perceptual and affective experiences afford further understanding of the affective values of humans with regard to products and services. In this study, we developed a method for the graphical modeling of texture-related perceptual and affective experiences, which were expressed by adjectives. The method enables the establishment of semantically causal relationships among the adjectives using the results of a standard sensory evaluation task based on adjective rating. The initial model was simplified by covariance selection to enable the definition of the causalities based on the assumption that the perception of the physical aspects of material surfaces produces affective and more personal experiences. For the purpose of validation through an experiment, we applied the developed method to the textures of 46 different flat materials and developed a model that was logically comparable to previously developed models. The proposed graphical modeling method promises to facilitate the design of product surfaces and an analysis of the subjective feelings induced by touching them.

Keywords: *Tactile sensations, Multilayered model, Covariance selection*

1. INTRODUCTION

Various internal responses are produced when humans touch material surfaces, which include psychophysical responses such as the perception of hard-soft or warm-cold, and affective and emotional responses such as the perception of modern-classic, sharp-dull, or delicate-bold. Figure 1 is a semantically multilayered causal model of the relationships among these texture-related responses. The model constitutes a map of the causes and effects of the human responses. An understanding of this causality is beneficial to the tactile design of commercial products in which the surface texture determines the affective value and constitutes a design factor. Such products comprise the packaging materials for food and general items [1], and seat fabrics [2]. Previous studies [1-8] agree that the upper layers of such a model contain the more affective factors, which are affected by integrated multiple sensory cues and individual knowledge, while the lower layers contain responses that are largely dependent on the perception of physical stimuli.

However, there are insufficient previous studies on such hierarchical models. The most prominent issue in this regard is that the approaches most commonly employed in affective engineering rely on multivariate analyses based on correlation matrices (e.g., factor analysis and structure equation modeling), and do not determine the causalities among the related factors, although they may enable an estimation of the causalities based on the correlations among the factors.

Thus far, several studies have been conducted to build multilayered causality models of texture-related adjectives [1-7]. However, a standard method is yet to be established. Some research groups [2-5] have classified human internal responses into affective and psychophysical layers and occasionally connected the responses included in the two layers by multivariate analyses. They, however, did not discuss the features of the layered structure, such as the number of layers. Moreover, because the affective layer may have a complicated structure composed of a few sublayers [1,6,7], the arbitrary design of the number of layers and items in each layer is a risky approach. Chen et al. [1] performed a rating task in which material textures were scaled using

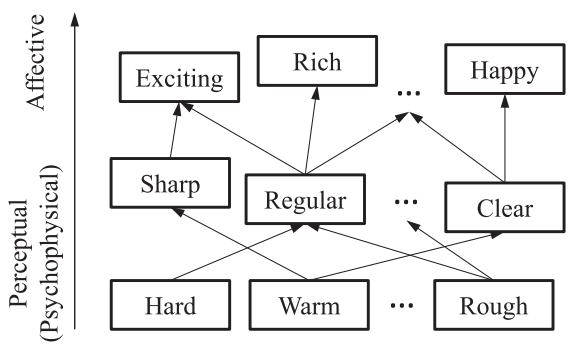

Figure 1: Multilayered causality model of perceptual, affective, and preferential responses to tactile textures. A directed arc indicates causality between two nodes.

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adjectives as the criteria, and produced a three-layered causality model of adjectives based on the correlations among them. However, the method was not elaborated upon and might have involved a heuristic approach. In contrast, Nagano et al. [6, 7] developed a causality modeling method based on the mutual impacts of the adjectives instead of the correlations among them. In these studies, the participants assessed the direction and magnitude of the impact of one adjective on another. Unfortunately, such an approach is not widely used in the field of affective engineering. A similar approach was also adopted by Munechika and Miwa [8], who considered food quality. The challenge is therefore to automatically build a hierarchical model using standard sensory evaluation methods. To address this issue, we developed a graphical method for modeling the hierarchical causalities among adjectives based on the results of a standard sensory evaluation task in which human responses to stimuli were typically rated using five or seven adjective scale grades.

To the best of our knowledge, ours is the first study to undertake the development of a method for building a hierarchical causality model of texture-related human responses based on adjective-rating tasks. The procedures of the method are outlined in Section 2 of this paper, and the underlying principles are described in Sections 3 and 4. Finally, in Section 5, through an experiment involving university students as participants, we present an example of the graphical model comprising 29 adjectives and 46 types of material samples and discuss the quantitative and qualitative validity of the model.

2. OUTLINE OF DEVELOPED METHOD

Here, we outline the procedures of the developed modeling method, which is summarized in Fig. 2.

Users of this method perform a standard sensory evaluation task to rate target materials using adjectives. The employed adjectives are those related to the perception of physical properties, such as rough-smooth and soft-hard (psychophysical descriptors), and those related to affective and personal experiences, such as modern-classic, friendly-unfriendly, and exciting-boring. Each adjective score is treated as a characteristic variable of the material. This sensory evaluation task yields a matrix that incorporates a partial correlation coefficient of an arbitrary pair of adjectives. Hence, as shown in Fig. 2A, the results of the sensory evaluation task can be expressed as a complete graph in which the adjectives and the magnitudes of the partial correlation coefficients are represented by nodes and arcs.

Covariance selection is then used to simplify the relationships among the adjectives while macroscopically retaining their correlation matrix. As shown in Fig. 2B, the arcs between weakly connected nodes are eliminated. This process enables a focus on the strong direct relationships among the adjectives.

A correlation model simplified by the above covariance selection (Fig. 2B) does not explicitly reflect the causal relationships among the adjectives. We therefore determined the direction of the effect or causality between two adjectives based on prior specific knowledge of tactile textures, namely that psychophysical adjectives semantically influence affective adjectives [1-8]. We allocated psychophysical adjectives to the bottom level of the hierarchy and each of the other adjectives based on the distance from the psychophysical adjectives at the bottom level. As shown in Fig. 2C, the impact of the psychophysical layer on an adjective and the closeness of the adjective to the bottom layer increases with decreasing distance between the adjective and the psychophysical layer.

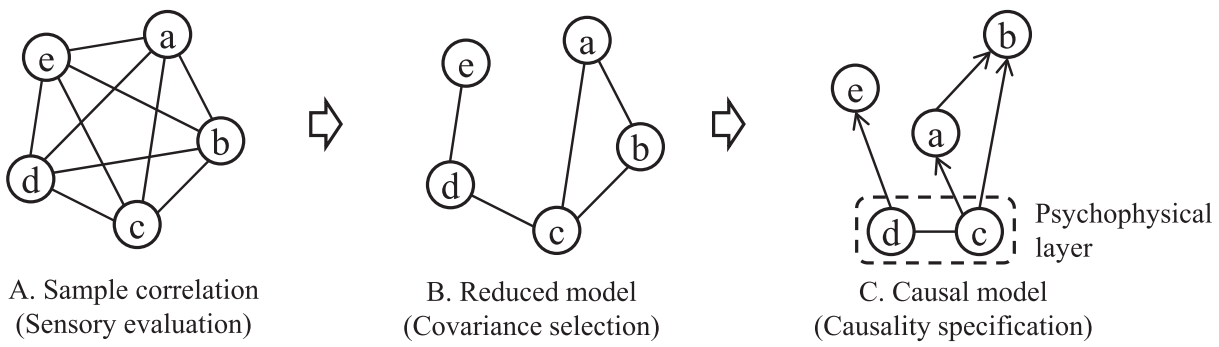

Figure 2: Procedures for establishing the multilayered causal model of texture-related perceptual, affective, and preferential responses. Each node corresponds to an adjective dyad used in the adjective-rating task. A) The correlation matrix is graphically expressed as a complete graph. B) Some weak connections are eliminated by covariance selection. C) The causalities between nodes are defined based on prior knowledge of texture-related perceptions and affections.

3. COVARIANCE SELECTION

The results of the sensory evaluation task provide the partial correlation coefficients among all the possible adjective dyads, and their graphical structure is exhaustive, as shown in Fig. 2A. Covariance selection [9, 10] is used to obtain a simplified structure (Fig. 2B), the correlation matrix of which is not statistically different from the sample correlation matrix. When the partial correlation coefficient between two variables is nearly zero, the variables are assumed to be independent of each other, and the arc between them is removed. Because each partial correlation matrix has a unique correlation matrix, the correlation matrix is computed from the reduced model. Provided that the correlation matrix of the reduced model is statistically consistent with the sample correlation matrix, the model can be continuously reduced. Typically, the model is continuously reduced until a reasonably practicable form is achieved. The covariance selection procedure is described below.

Here, Ω is a set of index pairs (i,j) of correlation or partial correlation coefficients $(1 \le i < j \le q)$, q is the number of observed variables (or adjectives), and $\hat{r}_{\mathrm{ij.rest}}$ is an estimate of a partial correlation coefficient between variables i and j. Ω is divided into two exclusive subsets I and J. For $(i,j) \in I$, $\hat{r}_{\mathrm{ij.rest}} = 0$ and for $(i,j) \in J$, $\hat{r}_{\mathrm{ij.rest}}$ has an arbitrary value. According to the theorem presented by Dempster [9], the maximum likelihood estimate $\hat{\boldsymbol{R}}$ of a sample correlation matrix $\boldsymbol{R}$ satisfies the following two conditions:

$$\hat{r}_{\mathrm{ij.rest}} = 0 \text{ for } (i,j) \in I, \text{ and}$$
$$\hat{r}_{\mathrm{ij}} = r_{\mathrm{ij}} \text{ for } (i,j) \in J$$

where r_{ij} and $\hat{r}_{\mathrm{ij}}$ are respectively a sample correlation coefficient between variables i and j and its estimate. In the present study, a correlation matrix that satisfies these conditions was computed using the iterative algorithm of Wermuth and Scheidt [11]. The corresponding partial correlation matrix of the computed one was forced to set some elements to zero.

In each step, one partial correlation coefficient with a small magnitude is set to zero, and the corresponding correlation matrix $\hat{\boldsymbol{R}}$ is computed and compared with the sample correlation matrix $\boldsymbol{R}$ to determine whether the reduced model is statistically congruent with the observed facts. By repeating this procedure, a simplified model that captures the sample correlation matrix is obtained.

Two types of indices are used to test the deviance between any two obtained models. Unless either type of index is adjudged to be large, the model is continuously reduced.

The deviance between a reduced model RM and the original full model FM is defined by $\boldsymbol{R}$ and $\hat{\boldsymbol{R}}$:

$$\mathrm{dev}(RM) = n \log \frac{|\hat{R}|}{|R|} \tag{1}$$

where n is the number of sample materials or products to be investigated. The distribution of dev(RM) asymptotically follows a chi-square distribution. Its degree of freedom is the number of partial correlation coefficients set to zero.

When a reduced model RM_{k+1} is derived from RM_k by setting the non-zero parameter of the latter to zero, the other deviance index is used to test the significance of the parameter:

$$\mathrm{dev}\left(RM_{\mathrm{k+1}}\right) - \mathrm{dev}(RM_{\mathrm{k}}) \tag{2}$$

The value of this deviance index also asymptotically follows a chi-square distribution with one degree of freedom.

In the present study, we used reference p values of 0.50 and 0.20 to judge the above two types of deviance indices, respectively. These p values are used in practice as criteria for model selection [10]. If the calculated p values are larger than the reference two values, the deviances are deemed to be minute.

4. CAUSALITY MODELING BASED ON DISTANCES FROM PSYCHOPHYSICAL LAYERS

As shown in Fig. 2B, a reduced model is obtained by covariance selection. This model is relatively simple and easy to understand compared to the complete graph in Fig. 2A. Nevertheless, while the partial correlation coefficients reflect the covariant properties of the variables, their causality remains unknown. Typically, prior specific knowledge of the problem is used to further analyze the causality. A temporal order of the events and the physically or chemically evident causality may be used for this purpose. However, this is clearly not applicable to human perceptual, affective, and preferential responses. There is thus the question of what may be considered as prior knowledge of tactile textures.

Many researchers hold that psychophysical human responses underlie the semantic space of perceptual and affective responses [1-8]. Psychophysical responses involve the perception of the sensory aspects of the physical properties of textured surfaces and can be expressed by adjectives such as, rough, warm, and hard. From the viewpoint of product design, it is reasonable to position these responses at the bottom of the model and to consider them as the causes of other affective and preferential responses. This is because the physical qualities of a product are variable and directly influence human psychophysical responses. In contrast, the affective or preferential responses that

are positioned higher in the hierarchy are less affected by physical stimuli of the product surface. Those positioned in the upper layers are more weakly connected to psychophysical responses. We therefore allocated the non-psychophysical adjectives with respect to their respective distances from the bottom psychophysical layer.

With regard to tactile texture perception, the psychophysical aspects of a surface are characterized based on the perceptions of macroscopic and fine roughness, softness, friction, and warmness [12-16]. As described in Section 5, uneven-flat, rough-smooth, hard-soft, sticky-slippery, wet-dry, and warm-cold were the psychophysical adjective dyads of our example application of the proposed modeling method. As also shown in Fig. 3, we allocated these adjective dyads to the bottom of the model and computed the strength of the connections among the psychophysical adjectives and the other adjective dyads. We used the determination coefficient of a linear regression analysis, wherein the ratings assigned to the non-psychophysical adjective dyads and the psychophysical ones were considered as objective and explanatory variables, respectively. If the rating of an adjective dyad j is denoted by y_j, and those of the six types of psychophysical adjective dyads are given by $\boldsymbol{x}=[x_1,x_2,x_3,x_4,x_5,x_6]^{\mathrm{T}}$, the regression model can be expressed as

$$y_i = \boldsymbol{a}^T\boldsymbol{x} \tag{3}$$

where $\boldsymbol{a}=[a_1,a_2,a_3,a_4,a_5,a_6]^{\mathrm{T}}$ is the vector of the regression coefficients for the six types of psychophysical adjectives. A larger determination coefficient indicates that the objective adjective dyad can be more directly explained by the psychophysical layer. A smaller coefficient means that the objective adjective dyad is also affected by factors other than the psychophysical ones, or that there may be a nonlinear relationship between the objective adjective dyad and the psychophysical layer. The use of the determination coefficient to establish the hierarchy of the adjective dyads enables an expression of how the affective factors are deployed in the upper layer and are affected by the psychophysical and other factors.

5. EXAMPLE OF GRAPHICAL MODEL OF TEXTURE-RELATED RESPONSES

We applied the proposed modeling method to the results of an adjective-rating task performed by Nagano [17] and validated the established causality model by comparison with those of previous studies. The experimental protocol was approved by the internal review board of the Engineering School, Nagoya University (Registration No. 12-6).

5.1 Material sample rating task

1) Methods:

The material surfaces were rated based on 29 perceptual and affective adjective dyads. Each of the adjective dyads comprised two semantically opposite adjectives, as listed in Table 1. The adjectives were selected from related studies (e.g. [3]) with care taken to avoid the duplication of similar descriptors. The adjectives were expected to cover the dimensions that form each semantic layer. The psychophysical [12], emotional [1-7], and preferential layers comprise at least five, two or three, and one (like/dislike) dimensions, respectively. The 29 adjective dyads used in the present study embodied these dimensions. Furthermore, they included typical adjectives such as rich, modern, and beautiful, which are used to judge the values of materials and products.

Each participant was blindfolded and acoustically masked with headphones that played pink noise, and

Table 1: Adjective dyads used for the sensory evaluation task

Beautiful/Ugly	Clean/Dirty	Clear/Vague
Comfortable/Uncomfortable	Concrete/Abstract	Dangerous/Safe
Delicate/Bold	Exciting/Boring	Friendly/Unfriendly
General/Special	Good/Bad	Happy/Sad
Hard/Soft	Interesting/Uninteresting	Itchy/Not itchy
Like/Dislike	Modern/Classic	Natural/Artificial
Regular/Irregular	Rich/Poor	Rough/Smooth
Sharp/Dull	Significant/Insignificant	Simple/Complex
Sticky/Slippery	Strange/Usual	Uneven/Flat
Warm/Cold	Wet/Dry	

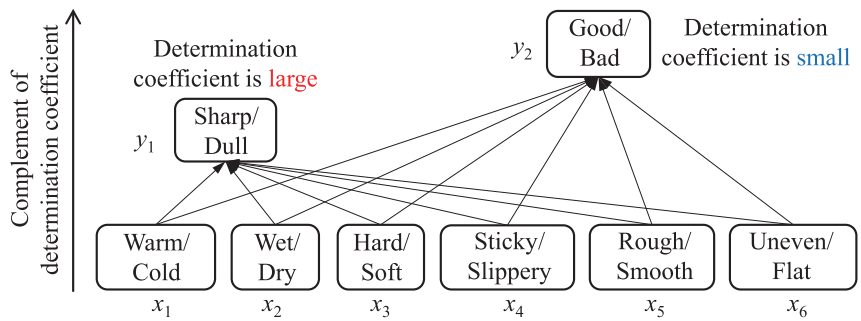

Figure 3: Specification of the causal relationships based on the determination coefficient of the regression analysis using six psychophysical adjectives as the explanatory variables

was required to touch and rate each material using 29 different seven-grade visual scales corresponding to the 29 considered adjective dyads. Each of the two semantically opposite adjectives was written in Japanese and English at either end of each visual scale. The allocation of the words was randomized among the trials. The participant touched each material on a desk using his/her one hand and was not allowed to lift or bend the material. No time limit was set for each trial because the number of adjectives to be considered for the rating was large. For the same reason, the participants were allowed to touch the material sample while doing the rating. They were nevertheless encouraged to do the rating without contemplation. The participants were not informed of any specific use of the materials. The order in which the materials were presented to the different participants was also randomized.

2) Material stimuli:

The experiment considered the 46 types of flat materials listed in Table 2. Each material sample was cut into a 90×90 mm square and attached to a hard plastic plate. The materials, which included wood, metal, cloth, ceramic, and plastic, were selected to uniformly cover the entire spectrum of tactile textures [12]. It should be noted that the results of this type of sensory evaluation task is dependent on the set of material samples, and it was thus not our intension to draw a general conclusion or establish a general model by the sample task.

3) Participants:

The participants were recruited by internal advertisements and comprised seven male and four female Japanese university students without any known tactile disability. Each signed an informed consent document.

Table 2: Forty-six materials used for the sensory evaluation task

Magnolia wood	Oak wood	Sapelli wood
Cork board	Fine woven straw	Coarse woven straw
Woven linen	Woven rush grass	Soft fake fur
Short hair fake fur	Long hair fake fur	Fake boa
Fake cowhide	Fake alligator hide	Fake woven leather
Fake suede	Felt	Towel
Satin	Pyramid rubber matting	Mirror plate
Iridescent sheet	Aluminum foil cloth	Mosaic tile
Glossy vinyl sheet	Glossless vinyl sheet	Cotton cloth
Denim	Fine Japanese paper	Crumped paper
Corrugated paper	Wall paper	Artificial grass
Sponge	Perforated aluminum	Woven wire mesh
Glass-beads-filled surface (7 mm diameter)	Glass-beads-filled surface (5 mm diameter)	Glass-beads-filled surface (3.5 mm diameter)
Glass-beads-filled surface (1.5 mm diameter)	Cotton	Goose feathers
Steel wool	Stainless steel scrubber	Urethane resin
Ceramic tile		

Although there were individual distinctions among the semantic structures of the psychophysical and emotional layers [7], the present discussion considers the average results of all the participants, as was done in some previous works [1, 2, 4-6]. Furthermore, one of the objectives of this study was to validate the proposed graphical modeling method by comparing the average results of the present experiments with those of previous studies, rather than discussing individual uniqueness. This justifies the use of the average results. However, a concern was whether the average results for 11 participants were representative for the local population. Hence, using the cross-validation method, we conducted a post-hoc test to determine whether the average covariance matrix computed from the 11 participants converged. Using the deviance index (1), we compared two types of average matrices: one was the average matrix for the 11 participants and the other was the average matrix for ten participants excluding an arbitrary participant. No significant difference was observed between the two matrices, indicating that the average matrix was not significantly modified by any one of the 11 participants.

4) Data analysis:

The adjective dyad ratings by each participant were transformed into z-scores and the average z-score for each material was then obtained.

5.2 Results: Graphical model of adjectives

We applied covariance selection to the results of the abovementioned sensory evaluation task to obtain a simplified model comprising 29 adjective nodes and 215 non-zero partial correlation coefficients. Overall, 191 arcs were removed from the full model of all the 406 relationships among the adjective dyads. As described in Section 4, the adjective nodes were positioned based on their respective distances from the bottom psychophysical layer. We then directed the effect between two nodes from the node in the lower layer to that in the upper layer. The hierarchical model shown in Fig. 4 was thus obtained. For visual clarity, the horizontal coordinates of the nodes were determined as follows. We obtained the distance matrix $\boldsymbol{D} = (d_{\mathrm{ij}} = 1 - |r_{\mathrm{ij.rest}}|)$ in which each element was the complement of an absolute partial correlation coefficient. Torgerson's multidimensional scaling method [18] was applied to $\boldsymbol{D}$, and the obtained coordinates of the most prominent dimension were used as the horizontal coordinates of the adjective nodes. Hence, the partial correlation coefficients between adjective nodes close along the horizontal axis were relatively large.

The model in Fig. 4 shows only the major arcs between nodes. The type of directed arc indicates the magnitude of

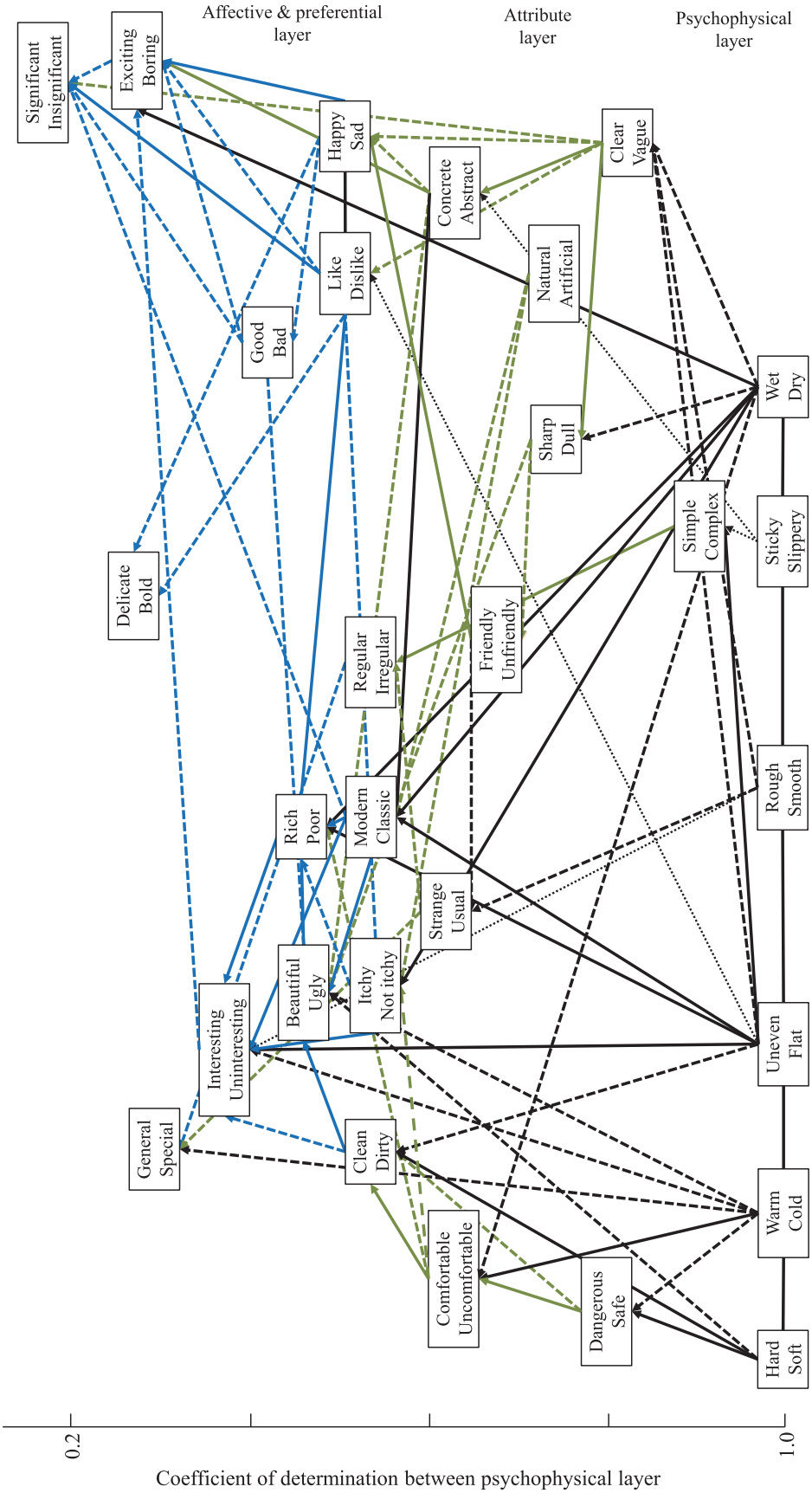

Figure 4: Graphical model of texture-related human responses.
The line type indicates the magnitude of the partial correlation coefficient. The solid, dotted, and fine dotted lines respectively indicate the coefficient values greater than 0.4, 0.3, and 0.2. Those from the bottom (psychophysical), middle (attribute), and top (affective and preferential) layer are black, green, and blue, respectively.

the partial correlation coefficient. Arcs whose absolute coefficients are greater than 0.3 and one of the three largest coefficients related to a node are drawn with black, colored solid, and dotted lines. The fine dotted arcs are those with absolute coefficients between 0.2 and 0.3 and are either the largest or second largest coefficients related to a node. When two nodes are located at vertically close positions, an undirected arc, which is equivalent to a bidirectional arc, was used to indicate the vague causality.

5.3 Qualitative validity of model

1) Overall structure:

First, we focused on the overall distribution of the adjectives. By principle, the psychophysical adjectives were in the bottom layer. The low and middle layers contained the descriptors related to the physical attributes of the materials, such as simple-complex, dangerous-safe, sharp-dull, regular-irregular, itchy-not-itchy, and natural-artificial. The middle-to-upper layers contained the affective and qualitative adjectives such as modern-classic, beautiful-ugly, rich-poor, exciting-boring, general-special, happy-sad, and interesting-uninteresting. Preferential words such as like-dislike and good-bad were also among the affective adjectives but were not clearly separated from the affective adjectives.

From another perspective, the lower layers included the adjectives with clear physical causalities, while the upper layers embraced the adjectives that do not basically characterize materials. For example, a dangerous-safe rating significantly varied with a hard-soft rating, based on which it is naturally inferred that the participants might have adjudged harder materials as being more dangerous, and softer ones as being safe. The simple-complex rating was strongly associated with that of uneven-flat, suggesting that the macroscopic surface roughness might have been perceived as being complex. Comfortable-uncomfortable was associated with warm-cold, indicating that the perceived warmness of a material might have induced comfort. In contrast, some adjectives in the upper level, such as exciting-boring and significant-insignificant, were weakly connected to the physical properties of the materials. These adjectives were thus located far from the psychophysical layer. The propagations of the effects were also depicted in the model. For example, uneven-flat was linked to simple-complex, and then to regular-irregular, and finally to general-special, indicating how the unevenness of material's surface affects its being perceived as special or general. Wet-dry affected rich-poor, which was in turn linked with like-dislike and good-bad. This indicates that materials such as artificial leather that feel wet were preferred because of their premium feel. Nonetheless, all the connections in Fig. 4 cannot be intuitively interpreted.

As mentioned above, the model indicates that the effects of the psychophysical factors are propagated to the affective and more qualitative ones, suggesting the semantic validity of the model.

2) Comparison with previous models:

A. Consistency with earlier studies: To assess the validity of the proposed method and developed model in the absence of a standard reference model, the present results of the model were compared with those of previously developed models. Table 3 presents the classification of the adjectives used in the previous studies. It should be noted that these adjectives were contained in discrete layers, as opposed to the continuous hierarchical structure of the present model.

Table 3: Comparison of the adjectives in each layer of the present and previous models.
The lower rows are lower layers. Because our model does not include discrete layers, the adjectives are grouped based on the vertical allocations in the model. The representative adjectives for [3, 4] are listed.

Present model	Nagano et al. [6,7]	Chen et al. [1]	Guest et al. [3]	Ackerlay et al. [4]	Matsuoka et al. [2]
Significant	Rich, good, happy, like	Playful, pleasurable, sophisticated, premium, precious, exciting	Enjoyable, irritating, comfortable, exciting, sexy, relaxing, calming, sensual	Relaxing, calming, pleasurable, comfortable, enjoyable, uncomfortable, irritating, sensual, arousing	Genuine, high-quality, luxurious, elegant, calm, adult, simple, casual, delicate, high-class
Exciting, delicate, general, interesting	Beautiful, friendly, interesting, significant, comfortable				
Beautiful, rich, good					
Clean, itchy, modern, regular, like, happy		Natural, indulgent, sensual, relaxing, delicate, simple			
Comfortable, strange, friendly, concrete	Concrete, general, dangerous, strange, delicate, simple, clear, delicate, regular				
Sharp, natural, clear, dangerous, simple					
Rough, uneven, hard, sticky, wet, warm	Rough, uneven, hard, sticky, wet, warm	Warm, rough, hard, sticky, dry	Hot-cold, rough (coarse)-smooth, sticky-slippery, hard-soft	Bumpy, lumpy, firm, hard, fuzzy, fluffy, hairy, wet, greasy, cold, slippery	Warm, hard, fluffy, thick, elastic, voluminous, bumpy, smooth, slippery, dry

Although the present and previous studies adopted different mathematical approaches and material specimens, their allocations of adjectives in the layered structures were largely consistent. However, detailed comparisons of the connections among the adjectives were either difficult or impossible because of the differences among the study objectives. Nevertheless, it was impressive that completely different methods involving rating tasks [1], word classification tasks [3], and semantic questionnaires [6, 7] produced similar results. This suggests that the layered structures of the adjectives were robust even though their detailed connections variably depended on factors such as the participants and types of materials used for the experiments. In other words, the layered structures were hardly affected by the experimental methods and mathematical analyses, suggesting a wide scope of potential applications.

B. Psychophysical layers: The locations of the psychophysical adjectives in the present model agree with those of previous studies [1-7]. This was due to an intentional attempt on our part to achieve consistency.

C. Comparisons with specific previous studies: Guest et al. [3] classified 168 adjectives used to describe tactile experiences into two layers without the performance of psychophysical material stimuli experiments. They found that the adjectives belonged to sensory or emotional classes and established a two-layered model of tactile textures. The upper emotional layer comprised comfortable-uncomfortable (e.g., pleasurable, calming, and irritating), arousing (e.g., exciting and relaxing), and stimulating (e.g., sensual, thrilling, and enjoyable) factors. Ackerley et al. [4] performed an experiment and analysis similar to those of Guest et al. [3]. Their upper layer comprised positive-negative emotions (e.g., relaxing, comfortable, uncomfortable, and irritating) and arousing factors (e.g., arousing, sensual, and exciting). The adjectives in the present model that are semantically close to the foregoing factors or descriptors, such as exciting-boring, comfortable-uncomfortable, happy-sad, and good-bad, were placed in the upper or middle layers without exception.

Chen et al. [1] proposed a three-layered model, the upper and middle layers of which were largely consistent with those of the present model. Their model was based on a sensory evaluation experiment involving 37 flat samples of materials that could be used to package food. The adjectives exciting, sophisticated, pleasurable, premium, and precious were placed in the top layer. In the present model, similar adjectives such as exciting-boring, happy-sad, delicate-bold, and rich-poor were placed in the middle or upper layer. The middle layer of the model of Chen et al. contained the adjectives natural and simple, which were located in the middle or lower layer of the present model. Conversely, adjectives similar to sensual, indulgent, and relaxing, which were placed in the middle layer of the model of Chen et al., were not used in the present experiment. Therefore, in terms of the locations of semantically comparable adjectives, the present model agrees well with that of Chen et al.

Nagano et al. [6, 7] built three- and four-layered models by specifying the causalities among the adjectives. The substantial similarity between their adjectives and those of the present study made comparison easy. Furthermore, they prepared the material samples in a manner similar to that of the present study. As can be seen from Table 3, there are no significant discrepancies between the results of the present study and those of Nagano et al., with the exception of general-special and delicate-bold. These two types of adjective dyads appeared in the second layer from the bottom in the model of Nagano et al., whereas they were included in the upper layer of the present model. Nagano et al. used the subjectively reported effects among the adjectives, whereas our model was based on the adjective scores for each of the materials. The determination of the consequences of this methodology difference requires further study. The adjectives general-special and delicate-bold have been rarely used in previous studies.

It is thus evident that the model developed in the present study largely agrees with those of previous studies in terms of the locations of the adjectives, and this validates the presently proposed method.

5.4 Quantitative validity of present model

Although the deviation between the full and simplified models was tested at every step of the covariance selection, it was beneficial to undertake the assessment from another perspective for validation purposes. The goodness of fit index (GFI) is a similarity index for comparing correlation matrices. The GFI value, which falls between 0 and 1 depending on the degree of match, with 1 indicating a perfect match, is given by

$$\mathrm{GFI} = 1 - \frac{\mathrm{tr}[(\hat{\boldsymbol{R}}^{-1}(\boldsymbol{R} - \hat{\boldsymbol{R}}))^2]}{\mathrm{tr}\left[(\hat{\boldsymbol{R}}^{-1}\boldsymbol{R})^2\right]} \tag{4}$$

The GFI value of the comparison of our simplified model with the original complete model was 0.77. Unfortunately, the previous studies cited in this paper did not use any similar index. However, the present GFI is fairly high, indicating that the original structure of the correlations among the adjectives was well retained. It should nevertheless be noted that the calculated GFI only validates the result of the covariance selection, and not the hierarchical structure of the model. This is because the index is based on the correlation matrices.

6. DISCUSSION

The modeling method developed in this study was confirmed to be valid for the data acquired from the experiment. Nevertheless, the method has some limitations, some of which are discussed below.

6.1 Model describes semantic, static, and linear causalities

Our graphical model does not describe neural subjective experiences because it is based on the results of a sensory evaluation task. It also does not consider the dynamics of the subjective experiences. For example, an upper layer may transiently affect lower layers, and the latter may be connected to the former in the response. Moreover, in the experiments, the participants were allowed sufficient perception time, which gives us reason to assume that the subjective reports potentially converged to certain internal states of the participants.

Considering the foregoing, we suggest that it would be effective not to specify the direction between the nodes when the restriction on a directional arc appears strong. In the model in Fig. 4, some arcs remain bidirectional and thus do not indicate causality between the nodes, but that the two nodes connected by an undirected arc co-vary. In the model, adjectives in the same layer are connected by undirected arcs. This is an option for the designer to mitigate the constraint of the model.

The present model is based on covariance selection and linear regression analysis of the adjective ratings. Both procedures linearly connect multiple variables, whereas human responses are intrinsically nonlinear. The established model is thus a linear approximation of a nonlinear system. Hence, the simultaneous application of the model or method to products or objects belonging to different categories should be avoided. Even broadly similar products such as cooking utensils, cutlery, and tableware should not be dealt with using the same model. Cutlery is typically made from metals, whereas tableware are often ceramic. Ceramic chopsticks or forks feel strange while ceramic dishes are widely acceptable. In other words, different products are perceived with different sense values. The proposed model should thus be developed and applied within good approximations.

6.2 Validity of causality model

The validation of the acquired causality model is demanding. The purpose of graphical modeling is to help analyze a system in which the relationships among multiple factors are not easy to comprehend. The methods for validating such models are limited. One effective method involves checking whether or not the model is semantically valid. Another method involves comparison of the model with previous models built by other experts. The present model was validated by these methods, as discussed in Section 5.3. It would be further convincing to use the present causality model to solve specific problems of real commercial products and services. This would demonstrate the potency of the proposed method.

7. CONCLUSION

The graphical modeling of the causalities among subjective human experiences, expressed by adjectives is typically done by performing sensory evaluation tasks. For the specific case of tactile textures, several models have been proposed [1-7], most of which comprised two layers, namely, psychophysical and affective layers [2-5]. However, a fundamental problem of these models is that the correlations among the experiences are not sufficient for adjudging the hierarchically causal structures of the adjectives. To resolve this problem, some previous studies investigated the subjective impacts among descriptive adjectives [6, 7]. However, a method based on a typical adjective-rating task is desirable for general application.

To summarize, in this study, we developed a method for building a multilayered graphical model of adjective dyads based on only the results of an adjective-rating task. The acquired correlations among the adjectives were simplified by covariance selection. The adjectives were then respectively positioned in the different layers based on the premise that psychophysical responses positioned in the bottom layer semantically propagate to other types of responses in the upper layers. We applied the method to 46 types of materials and 29 adjective dyads. The established model was shown to be quantitatively valid in terms of its good retention of the original correlation matrix, and semantically valid in terms of the respective locations of the adjectives.

The developed method is applicable to typical rating tasks using adjectives, and generally does not require the performance of special experiments. The method is expected to contribute to the manufacturing of affective products.

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REFERENCES

1. X. Chen, C. J. Barnes, T. H. C. Childs, B. Henson, and F. Shao; Materials' tactile testing and characterization for consumer products' affective packaging design, Materials and Design, 30(10), pp.4299-4310, 2009.
2. T. Matsuoka, H. Kanai, H. Tsuji, T. Shinya, and T. Nishimatsu; Predicting texture image of covering fabric for car seat by physical properties, Journal of Textile Engineering, 54(3), pp.63-74, 2008.
3. S. Guest, J. M. Dessirier, A. Mehrabyan, F. McGlone, G. Essick, G. Gescheider, A. Fontana, R. Xiong, R. Ackerley, and K. Blot; The development and validation of sensory and emotional scales of touch perception, Attention, Perception & Psychophysics, 73(2), pp.531-550, 2011.
4. R. Ackerley, K. Saar, F. McGlone, and H. B. Wasling; Quantifying the sensory and emotional perception of touch: Differences between glabrous and hairy skin, Frontiers in Behavioral Neuroscience, 8, pp.34:1-34:12, 2014.
5. W. Fujisaki, M. Tokita, and K. Kariya; Perception of the material properties of wood based on vision, audition, and touch, Vision Research, 109, pp.185-200, 2015.
6. H. Nagano, S. Okamoto, and Y. Yamada; Semantically layered structure of tactile textures, In: M. Auvray and C. Duriez (Eds.) Haptics: Neuroscience, Devices, Modeling, and Applications, Part I, Lecture Notes in Computer Science, Springer, pp.3-9, 2014.
7. S. Okamoto, H. Nagano, K. Kidoma, and Y. Yamada; Specification of individuality in causal relationships among texture-related attributes, emotions, and preferences, International Journal of Affective Engineering, 15(1), pp.11-19, 2016.
8. M. Munechika and T. Miwa; A guideline for selection of evaluation words used in questionnaire of kansei quality, Quality, 30(4), pp.446-458, 2000.
9. A. P. Dempster; Covariance selection. Biometrics, 28(1), pp.157-175, 1972.
10. M. Miyakawa; Graphical Modeling, Asakura Shoten, 1997.
11. N. Wermuth and E. Scheidt; Fitting a covariance selection model to a matrix. Journal of the Royal Statistical Society, Series C (Applied Statistics), 26(1), pp.88-92, 1977.
12. S. Okamoto, H. Nagano, and Y. Yamada; Psychophysical dimensions of tactile perception of textures, IEEE Transactions on Haptics, 6(1), pp.81-93, 2013.
13. R. L. Klatzky, D. Pawluk, A. Peer; Haptic perception of material properties and implications for applications, Proceedings of the IEEE, 101(9), pp.2081-2092, 2013.
14. S. J. Bensmaïa; Texture from touch, Scholarpedia, 4(8), 7956, 2009.
15. W. M. Bergmann Tiest; Tactual perception of material properties, Vision Research, 50(24), pp.2775-2782, 2010.
16. J. van Kuilenburg, M.A. Masen, and E. van der Heide; A review of fingerpad contact mechanics and friction and how this affects tactile perception, Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology, 229(3), pp.243-258, 2015.
17. H. Nagano; Computational methods for combining perception, emotion, and behavior in haptic invitation and interaction, Ph.D. Thesis, Graduate School of Engineering, Nagoya University, Japan, 2015.
18. W. S. Torgerson; Multidimensional scaling: I. Theory and method, Psychometrika, 17(4), pp.401-419, 1952.

Kensuke KIDOMA (Non-member)

Kensuke Kidoma received a B.S. degree from Nagoya University in 2015. His research interests comprise multivariate analysis.

Shogo OKAMOTO (Non-member)

Shogo Okamoto received MS and Ph.D degrees in information sciences in 2007 and 2010, respectively, from the Graduate School of Information Sciences, Tohoku University. Since 2010, he has been with the Department of Mechanical Science and Engineering, Nagoya University, Japan. His research interests comprise haptics, human assistive technology, and wearable robots.

Hikaru NAGANO (Member)

Hikaru Nagano received B.S., M.S. and Ph.D degrees in engineering from Nagoya University in 2010, 2012, and 2015, respectively. Currently, he is an Assistant Professor in the Graduate School of Information Sciences, Tohoku University, Japan. His research interests comprise human perception and man-machine interfaces.

Yoji YAMADA (Non-member)

Yoji Yamada received a Ph.D. degree from the Tokyo Institute of Technology in 1990. He has been an associate professor at the Toyota Technological Institute, Japan since 1983. In 2004, he joined the National Institute of Advanced Industrial and Science Technology (AIST), as a group leader of the Safety Intelligence Research Group at the Intelligent Systems Research Institute. In 2008, he moved to the Graduate School of Engineering, Nagoya University, as a professor.