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Computational Methods for Combining Perception, Emotion, and Behavior in Haptic Invitation and Interaction

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Abstract

When a human touches a surface, a variety of internal responses are evoked, including perception and emotion. To specify the reliable common dimensionality for the perception of physical properties of materials is instrumental in understanding mechanisms of human percepts. In addition, the construction of the relationships between perceptual and emotional responses help in estimating various impressions for touched surfaces.

Touching is sometimes invited by a surface in daily life. The author refers to such a phenomenon as haptic invitation. To understand the relationships among degrees of haptic invitation, perceptual responses and invited behaviors is potentially useful for designing products that invite human touch motions and stimulate human interest.

This thesis developed computational and construction methods for relationships among perceptual, emotional, and behavioral responses of human, which is composed of six chapters. Chapter 1 is the introductory chapter. Chapter 2 addresses a study on the identification of a common structure of psychophysical dimensions for perceptual responses. Chapter 3 is a study on the development of a construction method for a multi-layered model of perceptual, affective, and hedonic responses. Chapter 4 is to identify perceptual responses for materials and physical properties of materials that affect degree of haptic invitation. Chapter 5 is a study on developing probabilistic relationships between invited behavioral responses and perceptual responses to materials. Chapter 6 is the concluding chapter. Individual chapters are outlined below.

In chapter 2, a common structure of psychophysical dimensions for perceptual responses was found. Although many studies have constructed the psychophysical spaces for materials, the spaces constructed in these studies have varied depending on the difference in experimental conditions such as experimental methods, analytical methods, materials and words used in the experiments. Therefore, this chapter investigated as many

related studies as possible to specify the common structure of psychophysical spaces, and summarized experimental and analytical methods to discuss their limitations. In addition, the relationships between the established common spaces and the mechanisms of each psychophysical dimension were also explained. The five dimensions represented by "rough/smooth," "flat/bumpy," "warm/cold," "hard/soft," and "sticky/slippery" adjectives were frequently extracted. In addition, the mechanisms of these five types of perception are different. Thus, the author reasonably summarizes that common dimensions for perceptual responses to materials consist of the five dimensions such as macro roughness, micro roughness, warmness, hardness, and friction.

In chapter 3, a construction method for a multi-layered model of psychophysical, affective, and hedonic responses was developed. Although relationships between psychophysical responses and physical properties have been investigated by many earlier researchers, relationships between affective (emotional) or hedonic (preferential) responses and psychophysical ones have not yet been developed. Thus, it is difficult to predict the physical properties of materials or objects that affect emotional or preferential responses to them. A multi-layered model combines psychophysical, emotional, and preferential responses, which solves this difficulty. There is a problem that, for determining a structure of model of adjectives representing internal responses of human, causal information between adjectives is necessary. To solve this problem in a construction of a multi-layered structure, the causalities between adjectives were evaluated, which determined a structure of model. Next, unknown parameters including strength of relationships between adjectives in a constructed structure were statistically estimated using sensory evaluation and structural equation modeling. A computational method of a semantically multi-layered model expressing internal responses included above-described two processes. For the validation of the developed method, the author conducts experiments to construct a model representing the relationships between touch-related internal responses. The constructed model had the three types of layers including the adjectives that represented psychophysical, affective, and hedonic responses, which indicates that the developed method are available to construct a semantically multi-layered model of internal responses to a material set. In addition, several types of models could be constructed based on a single dataset of evaluated causalities using different thresholds values. The models had different number of nodes and arcs, and each model showed a different fitness for observed data. In this study, one constructed model demonstrated the good performance (CFI of 0.93) for representing the results of sensory evaluation. The developed method for connecting perceptual, emotional, and preferential words expressing touch-related internal responses will help design various impressions of product and analyze human percepts.

Chapter 4 developed a measurement and design method of haptic invitation that is a phenomenon that material surfaces invite human touch. Although haptic invitation can be applied to products that lure consumers' touches, poster advertisements that seek to grab the attention of a passersby, and art works that motivate the audience to touch them, nobody knows what kind of properties of materials invite human touches. The appearance of a material may be related with the degree of haptic invitation for the material. In addition, a degree of haptic invitation is possibly determined through human sensory processing. Physical properties of materials and human internal responses towards materials, which the author named visual and sensory factors are computationally connected with degrees of haptic invitation. Thus, this chapter establishes the relationships among visual and sensory factors for materials and degree of haptic invitation, which demonstrates the factors of materials that invite human touch and what extent a linear connection of these factors can describe degree of haptic invitation. The four visual factors are surface color, gloss, shape type, ridge-groove width, and the four sensory factors are dry, uneven, cold and simple factors. The degrees of haptic invitation are measured by a ranking system and the normalized-rank approach. Regarding the visual factors of textures, their glossiness and surface shape strongly affected the degree of haptic invitation. There was no correlation between their surface colors and the degree of haptic invitation for materials through further experimentation. Regarding the influence of sensory factors, dry and simple factors were observed to be strongly related to the degree of haptic invitation. Multiple regression analyses revealed that the visual and sensory factors effectively described the degrees of haptic invitation with accuracies of 68% and 75%, respectively.

In chapter 5, probabilistic relationships between invited touch motions and perceptual responses to materials were investigated. These relationships supported to investigate two propositions underlying the mechanism of haptic invitation. First, a material with a prominence in perceptual responses frequently invites human touch motions. Second, a invited touch motion is determined by the type of a prominent perceptual response. A series of experiments were conducted for constructing probabilistic and investigating mechanisms of haptic invitation, in which perceptual properties were evaluated through sensory evaluation and human touch motions invited by materials were observed. The degree of prominence was calculated based on the ratings for perceptual properties. To validate two propositions, several analyses were conducted. With regard to the first proposition, a positive correlation coefficient of 0.54 was observed between the degrees of haptic invitation and the indices of textural prominence. This coefficient increased to 0.63 in the case that the prominence values were calculated based on the factorial values that integrated the correlated textural properties. Furthermore, the degrees of textural prominence of materials that invited touch motions were higher than those of materials that were not touched. These results supported the first proposition. With regard to the second proposition, a Bayesian network model that represented the probabilistic relationships between the invited touch motions and the perceptual properties was constructed. The model corroborated the idea that invited touch motions and touch modes vary, depending on the different types of prominence in textures. As described above, perceptual prominence in textures tended to invite human touch motions, and types of prominent textures were likely to invite appropriate touch motions. Haptic invitation increases the probability that people will make contact with textures as haptic inputs, which can be sensed through economic motions for textures, unlike passive visual or auditory stimuli. The haptic invitation of material may be interpreted as a phenomenon in which the textural prominence of a material encourages human to feel it. One rational role of this phenomenon is to maintain the system whereby individuals recognize tactile textures, because the increase in the probability of touching prominent textures may be instrumental in activating human perceptual systems.

The methods for computation and construction of relationships between perceptual, emotional, and behavioral responses of human were developed through the studies in this thesis. The engineering utilization of psychophysical responses have been promoted based on relationships between psychophysical responses and physical properties of materials. The developed methods presents a new technical platform to design human emotional, hedonic, behavioral responses to material surfaces by controlling physical properties of the materials.

Contents

Chapter 1

Introduction

Human perceives several properties of a surface by touching. For example, surface roughness is mediated by stroking a finger on the surface. Tactile perception of physical properties of surfaces is essentially indispensable in a daily life, because it helps manipulating objects, distinguishing subjects, or recognizing the physical world. In addition to perceptual properties of surfaces, affective or emotional properties of surfaces also arise through skin sensation by touching. For example, when a human touches a surface like fur, s/he may feel it smooth, comfortable, and rich. A variety of human internal responses including perception and emotion arises in haptic interaction. This thesis regards haptic interaction as a framework that mixes perceptual and emotional responses to surfaces.

Haptic interaction is occasionally invited by a surface in daily life. For example, a elastic rubber may invite human pushing behaviors. The author refers to such a phenomenon as haptic invitation. Several types of behaviors such as pushing, rubbing, and stroking are elicited by perceiving visual properties of a surface in haptic invitation. The author treats behaviors invited by surfaces as behavioral responses to them, and that haptic invitation is a phenomenon combining perceptual responses to surfaces with behavioral responses to them.

This thesis focuses the relationships among perceptual, emotional, behavioral responses to surfaces. To understand such relationships among several would enable us to estimate or design the materials and objects that frequently invite human touch motions or give rise to several internal responses. Such surfaces are potentially useful for various purposes given that many researchers have reported favorable effects of touch on consumers' intentions when making purchases [1], evaluating products [2], and evaluating brands [3]. Furthermore, haptic invitation can be applied to products that have the potential to attract a consumer's touch, poster advertisements that seek to grab the attention of a passersby, and art works that seek to motivate the audience to touch them. However, such surfaces have not been widely used because the modeling methodology of relationships among perceptual, emotional, behavioral responses to surfaces have not yet been developed.

There are several studies focusing each type of perceptual, emotional, behavioral responses. Based on the findings of these related studies, the author find this thesis's approaches to investigation of relationships.

1.1 Internal Responses to Surfaces in Haptic Interaction

1.1.1 Related Studies on Perceptual Responses to Surfaces

The perception of physical properties such as smoothness, warmness, and hardness has drawn the interests of many researchers [4, 5, 6], and then many studies attempted to construct perceptual dimensions of physical properties of materials [7, 8, 9, 10, 11]. The dimensionality for perceptual responses is instrumental in understanding mechanisms of human percepts and in the design of multimodal tactile displays and sensors. To generalization of tactile dimensionality indicates which dimension should be considered for the studies on haptic percepts or haptic technologies. Although many studies have been conducted attempting to specify the psychophysical dimensions for perceptual responses to materials, specified dimensions have differed depending on study. For example, while Hollins et al. [12] reported that the psychophysical spaces consisted of the three dimensions respectively described by roughness, hardness, and slipperiness; however, Yoshida et al. [8] extracted four dimensions. In this thesis, before that the relationships among perceptual, emotional, and behavioral responses are investigated, a common structure of psychophysical dimensions for perceptual responses to material surfaces should be found.

1.1.2 Related Studies on Emotional Responses to Surfaces

Touching surfaces gives rise to both human perception of properties and emotions such as comfort. Many studies have focused on a multidimensional space for perceptual or emotional responses. For example, dimensionality in a psychophysical layer has been studied, such as in [7, 8, 10]. Okamoto et al. [13] reviewed psychophysical spaces that demonstrate the five common dimensions consisting of "rough-smooth," "uneven-flat," "hard-soft," "warm-cold," and "sticky-slippery." Similar opinions have been found in other studies [4, 5, 6]. Guest et al. [14] investigated each multidimensional space for psychophysical and affective responses. Although, a method for specifying a dimensionality in each of perceptual and emotional responses to surfaces have been established and used widely, a method for combining human internal responses such as perception, affection, and preferential responses has not yet been developed.

1.2 Behavioral Responses to Surfaces in Haptic Invitation

1.2.1 Related Studies on Behavioral Responses to Surfaces

Many researches addressed differences in touch motions or behaviors. Lederman and Klatzky [15] reported that hand movements varied during haptic object exploration, depending on the desired properties of objects, such as heaviness and hardness. In addition, hand dynamics and contact forces for these prototypical hand movements were quantitatively investigated by Jansen et al. [16]. Giboreau et al. [17] qualitatively assessed that textile experts used different types of gestures to evaluate different properties of fabrics. Whereas circular or linear finger movements are used to evaluate rough, relief, and slippery surfaces, localized pressure applied through fingertips is used to evaluate the softness and thickness of materials. In addition, other studies showed that motions or behaviors were related to textural perception. Gamzu and Ahissar [18] demonstrated that scanning velocities are adapted to the grating frequency. Kaim et al. [19] reported that both contact forces and velocities are affected by the pliability of objects. The relationships between the perceived roughness of surfaces and contact forces [20, 21] and those between surface friction and tangential forces [22] have also been investigated. However, the relationships between texture-invited touch motions and textural properties have not been thoroughly investigated. The differences in invited touch motions or behaviors are likely related to the mechanism of haptic invitation and should be considered.

1.2.2 Related Studies on Desire to Touch

The desire to touch products for hedonic reasons was studied by Peck et al. [23, 24]. They proposed an index named "need for touch" which measured individual preferences for touching products from two aspects. One is a goal-oriented aspect in which customers touch and hold products in order to decide their purchases. The other is a hedonic-oriented aspect [25] in which customers feel inclined to touch products for fun. A index for personal preferences that indicates the extent to which extent a person tends to touch products has been developed, which differs from a index for material characteristics that indicates the extent to

Klatzky et al. [26] investigated the extent to which 3D objects invited human touch using a "touch-ability" index, which averaged two kinds of ratings. The first rated objects with regard to the statement "this object invites me to touch it." The second rated objects with regard to the statement "touching this object would feel good." The coefficient of correlation between these ratings was approximately 0.9, indicating that these scales were quite similar. Klatzky et al. measured touch-ability for 3D objects displayed as images, which were about the size of a ping-pong ball or a tennis ball. Thus, "touch" implicitly included both grasping and stroking the surfaces. The object's material was described as concrete or glass in the questionnaire, and reflectance properties such as the bidirectional reflectance distribution function did not appear to be integrated into the object design. The ratings for glass were higher than those for concrete. Objects of moderate shape and texture were preferred while those with significantly rough textures or edgy shapes generated smaller scores. Although Klatzky et al. have focused the shape of objects, this thesis's objective is instead to investigate the properties of materials that invite human touch.

1.3 Research Objectives

1.3.1 Psychophysical Dimensions of Perceptual Responses to Surfaces

The structure of psychophysical dimensions or spaces for perceptual responses to surfaces are necessary to understand the mechanism of human percepts. However, the spaces constructed in the earlier studies have varied depending on the difference in experimental conditions such as materials or words. The author attempts to find a common structure of psychophysical dimensions for perceptual responses to material surfaces in Chapter 2 as shown in Fig. 1.1.

In Chapter 2, the author investigates as many related studies as possible to find the common dimensionality for perceptual responses to materials, and summarizes experimental and analytical methods to discuss their limitations and effective uses. In addition, the relationships between the dimensions found as common factors representing perceptual properties of materials and the mechanisms of such psychophysical perception are also discussed.

1.3.2 Multilayered Relationships Among Internal Responses to Surfaces

A human touches a surface, a variety of internal responses are evoked, including perception and emotion. The information space of such perception or emotion is often regarded as a multilayered space consisting of three types of words that respectively represent psychophysical, affective, and hedonic responses [27, 28, 14, 29].

A multilayered model of human internal responses, exemplified in Fig. 3.1, is instrumental in estimating human affective and hedonic reactions to products. Such a multilayered model combines the responses of a high layer with those of a low layer. For example, "happy-sad" ratings are affected by "comfortable-uncomfortable" and "interesting-uninteresting" ratings, while "comfortable-uncomfortable" and "interesting-uninteresting" ratings are affected by "rough-smooth," "uneven-flat," and "hard-soft" ratings. The relationship between psychophysical perception and physical properties of materials has been identified in many studies, such as [27, 30, 31]. Using the knowledge of these literature, a multilayered model enables us to estimate physical properties that affect human responses in higher layers.

A multidimensional space representing multiple layers of internal responses to materials or objects has not yet been investigated. Many studies have focused on a multidimensional space in a single layer, they did not construct these spaces. Ueda et al. [32]

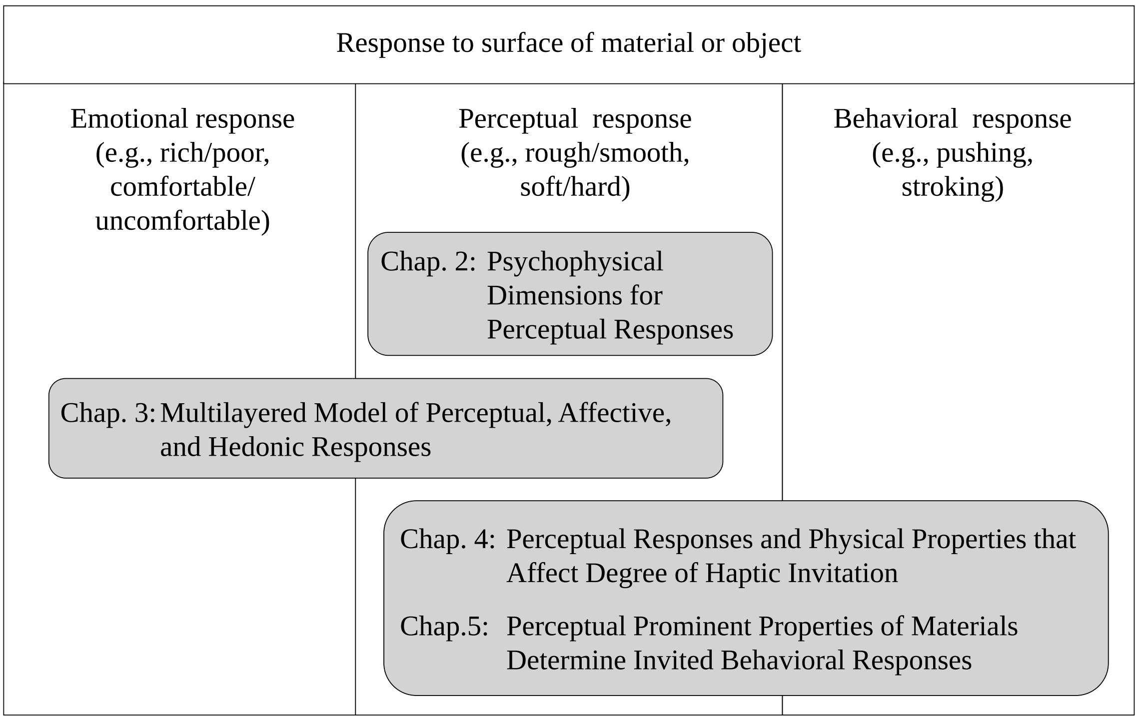

Fig.1.1 Four chapters addressing perceptual, emotional, behavioral responses to surface of material or object

represented words according to the rating for semantic abstractness, which is handled as a layered space. Nevertheless, causal relationships between words were not considered. Chen et al. [28] constructed a multilayered relationship among adjectives representing tactile textures based on the correlation matrix among the ratings for the adjectives. However, it is difficult to define a causal relationship among adjectives according to a correlation matrix, thus they did not constructed a multilayered model covering a causal relationship. As described above, a systematic method for constructing a multilayered model of human perception, affection, and preferential words has not yet been developed. Therefore, the author develops the construction method for a multilayered model in Chapter 3 as shown in Fig. 1.1.

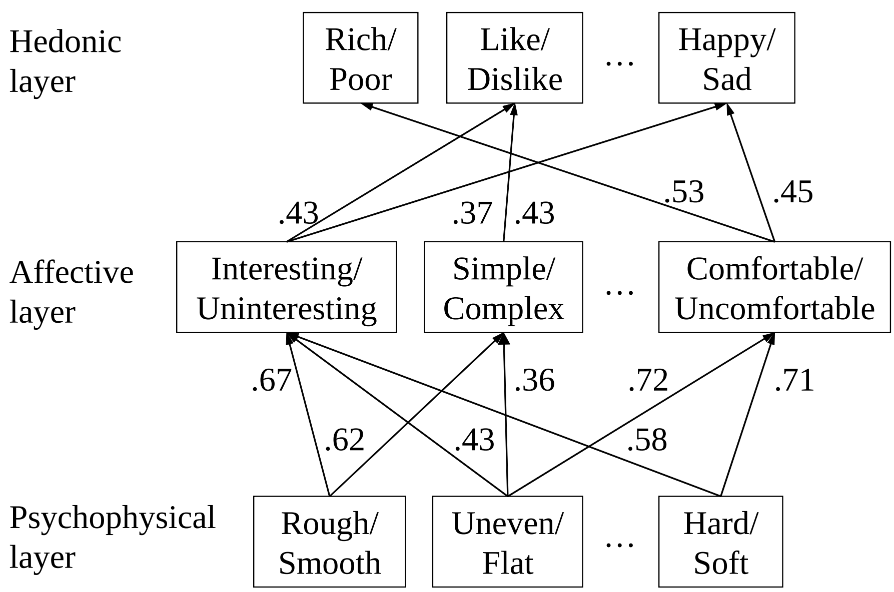

Fig.1.2 Concept of semantically layered model of adjectives representing internal responses

1.3.3 Relationships Between Perceptual Responses to Surfaces and the Degrees of Haptic Invitation

There have been many studies on the effects of the physical and perceptual aspects of materials or objects on human perceptions and feelings. Relationships between the physical and perceptual properties of materials have been investigated [31, 33]. For a purpose of product design, Winakor et al. studied the effect of the physical properties of textiles on customer preferences for woven cotton and polyester fabrics [34]. Relationships between materials and preferences with regard to wrapping paper [27], sleeping wear [35], and car sheets [36] have also been studied. Kawabata et al. proposed a method for predicting human preferences for clothing fabrics from their physical properties [30]. As described above, many researchers have worked on the relationships between the physical and perceptual properties of materials as well as their effects on product preferences. However, the relationships between the physical and perceptual properties of materials and the degree of haptic invitation have not yet been investigated. In Chapter 4 as shown in Fig. 1.1, the author establishes a statistical index that represents the degree of haptic invitation and the relationships between factors of materials and degree of haptic invitation. The relationships would support human to determine the best combinations among limited factors in terms of degree of haptic invitation in product design.

1.3.4 Relationships Between Perceptual Responses and Behavioral Responses to Surfaces

The methodologies in Chapter 4 will enable us to design surfaces that appeal to human touch. However, it is still unknown exactly how people touch these surfaces. The author conjectures that the difference in invited touch motions may be a clue to elucidating some of the mechanisms of haptic invitation. Thus, in Chapter 5, the author constructs a stochastic model that represents the relationships between perceptual properties of materials and invited touch motions as shown in Fig. 1.1. The constructed model is potentially useful for estimation of human motions from properties of material surfaces. In other words, it is possible to design a material or an object that frequently invites specified touch motions.

Chapter 2

Psychophysical Dimensions of Perceptual Responses

Many studies have been attempted to specify the psychophysical spaces for perceptual responses to materials. However, specified dimensions have varied with study. The differences in specified dimensions may be depend on the difference in experimental method, analytical method, experimental materials. This chapter investigates as many related studies as possible to find the common dimensionality for perceptual responses to materials, and summarizes experimental and analytical methods to discuss their limitations and effective uses. In addition, the relationships between the found common dimensions and the mechanisms of such psychophysical perception are also discussed.

2.1 Methodology for Specifying Dimensions for Perceptual Responses

The methodologies used to specify the psychophysical spaces for perceptual responses to materials are consisted of two processes, in which the collection of subjective values for materials and multivariate analyses are conducted. Ratings for properties of materials using adjectives such as rough/smooth pairs or perceptual similarities between materials are frequently used for subjective data. Multivariate analyses extract perceptual dimensions from subjective data. The combinations of psychological and analytical methods used in related works are shown in Table 2.1. A circle or triangle represents more or less frequently used in related articles, respectively.

2.1.1 Psychophysical Methods: Collection of Perceptual Data

The author introduces the psychophysical methods used for collecting perceptual values for materials.

Semantic Differential (SD) method

SD method was developed by Osgood et al. [37], and firstly applied to the study on a tactile perceptual dimensionality by Howorth [7] in 1958. Since then, many researchers have used this method for specifying dimensions. In a SD method, participants evaluate materials using five or seven point scales as criteria for subjective evaluation. Each scale has an opposing pair of adjectives such as “rough” and “smooth.” Some studies used onomatopoeia instead of adjectives [38, 31].

In SD methods, an additional experiment to name dimensions is not necessary, which is typically necessary for other approaches without adjectives, because it is possible for us to interpret the dimensions by combinations of adjectives. On the other hand, there is a weak point of a SD method that extracted dimensions are limited by used adjectives.

Table 2.1 Combination of psychophysical and analytical methods for structuring perceptual spaces. Circle or triangle indicates more or less frequently used approaches, respectively.

	Factor analysis or principal component analysis	Multidimensional scaling
Semantic differential method	○	△
Similarity estimation method		○
Classification method		○

Thus, the adjectives covering all fundamental dimensions should be chosen. The number of adjectives is a burden for participants, which should not be ignored.

Similarity Estimation Method

In the similarity estimation, perceptual similarity or dissimilarity between two materials are evaluated. The three types of methods, which are grading, visual analog scaling, and ratio judgment, are typically used for evaluating similarity or dissimilarity. The ration judgment method enable us to evaluate the perceptual distances between stimuli [33]. The grading method is capable of evaluating the perceptual similarities between materials using a seven or five point scale [39, 9]. The visual analog scaling method allows participants to rate the perceptual distances between materials by marking a spot on a line with "dissimilar" and "similar" labels [40, 12].

Similarity estimation methods do not use adjectives. Hence, the number of extracted dimensions are not limited by adjectives, which is different from SD methods, The evaluated similarity or dissimilarity is typically analyzed by a multidimensional scaling (MDS) method. The main weak point of this method is related with the number of trials. Participants should evaluated the similarities between all pairs of materials. Therefore, experimenters have to prevent the number of materials from rising, which often lead to the result that limited numbers of dimensions are extracted.

Classification Method

Participants classify materials into groups according to the perceptual similarities or dissimilarities between the materials. The materials classified into same group are treated as similar. The experimenters evaluate dissimilarities between materials according to the results of classification. For instance, the dissimilarity score for same group's materials is evaluated as 0, whereas that for the materials in different groups is evaluated as 1. This method was used in [10, 11, 41, 42].

Ballesteros et al. used the free arrangement classification method that is similar to the classification method [43]. In this method, participants place stimuli on a plane, in which the distances between stimuli indicate a similarity or dissimilarity between the stimuli. This method limits the perceptual dimension to two-dimensions because constructed dimensions are based on location of materials on a plane.

In these methods, participants can test a sufficient number of materials because these have better efficiency from the point of view of experimental duration. It may be extreme to consider that the dissimilarity among the materials in a same group is 0. Furthermore, each material is classified into only one group. These assumptions may result in loss of some differences between materials.

2.1.2 Analytical Methods: Multivariate Analyses for Subjective Data

Factor Analysis (FA) or Principal Component Analysis (PCA)

A factor analysis extract factors based on correlations between evaluated subjective data. Although the number of extracted factors is lower than that of measured subjective data, the variance in the extracted factors explains most of the variance in the measured data. The combination of a factor analysis and a SD method is frequently performed. Subjective data $\boldsymbol{x}_i$ $(i = 1,...,n)$ that are collected for n materials using p adjective pairs are described as follows:

$$\underset{p\times 1}{\boldsymbol{x}_i} = \underset{p\times m}{\boldsymbol{A}}\,\underset{m\times 1}{\boldsymbol{f}_i} + \underset{p\times 1}{\boldsymbol{e}_i} \quad (i = 1,\cdots,n), \tag{2.1}$$

where $\boldsymbol{f}_i$, $\boldsymbol{A}$, and $\boldsymbol{e}_i$ are the scores of m factors, a factor loading matrix, and the scores of a unique factor, respectively. Each of the m factors is an independent factor. Principal component analysis (PCA) is similar to factor analysis, which is frequently used with the subjective evaluation obtained using SD methods. In a PCA method, the variance of lower number of factors effectively represents most of the variance of variables used in experiments.

Multidimensional Scaling (MDS) In a multidimensional scaling method, materials are located on r-dimensions based on the perceptual distances between the materials. Perceptual distances are optimally calculated using the evaluated data from similarity estimation or classification methods. There are some examples using SD methods [8, 44], in which the perceptual distances between materials were calculated using the data from SD methods

The coordinates of n materials on r-dimensions are optimally determined by

$$Q = -\sum_{j=1}^{n}\sum_{k=1}^{n} e_{jk} \parallel \boldsymbol{y}_j - \boldsymbol{y}_k \parallel^2, \tag{2.2}$$

where $\boldsymbol{E} = (e_{jk}|j \neq k)$, $(j,k = 1,...,n)$ and $\boldsymbol{y_j}$ are the matrix of similarity scores between materials and the coordinate of material j, respectively. Each of the r dimensions is treated as be a potential perceptual dimension.

The MDS method has a weak point that the orthogonal rotation of dimensions is indeterminate. In the related studies, it is often stated that an interpretation of results is difficult because of an indeterminate axis. An constructed axis does not always interpret an perceptual dimension. This inconvenient characteristic of the MDS method is often neglected.

The interpretation of extracted spaces is sometimes problematic. Although, for the data by SD method, the factor loadings of adjectives can characterize extracted spaces, the interpretation of extracted spaces based on the data by MDS method is necessary. The popular methods for interpretation are the method with adjectives and that with physical properties of materials.

In terms of the method using adjectives, participants evaluate materials with adjectives. The constructed spaces are interpreted according to the correlations between the scores for adjectives and the coordinates on the spaces. When the coordinates on a constructed dimension are strongly correlated with the ratings for "rough," it is interpreted that this dimension represents roughness perception. Validation using adjectives was conducted in [12, 10, 11, 45].

In therms of the method using physical properties of materials, the correlations between the measured physical properties and the coordinates on constructed dimensions are calculated. When the coordinates on a constructed dimension are strongly correlated with the average roughness of materials, this dimension is often interpreted as the dimension representing roughness perception. Validation using physical properties was conducted in [33, 40, 42].

2.1.3 Difficulty in Selection of Materials

As described thus far, multivariate analyses extract fewer factors that represent a large portion of the variance of variables used in collection of subjective data. When the distribution of used materials is imbalanced in common spaces, the space in which the variance of dimensional scores is low will be undetected. In terms of a balance of materials, while many studies used easily prepared materials such as paper, wood, and leather, sticky or moist stimuli are not often used. Although moist or sticky materials are not frequently used, paper, fabric, rubber, stone, or leather materials, which are easily prepared, are often used in experiments. If experimenters use easily-prepared materials, the dimension representing moist or adhesive perception will not be extracted. None of the studies adopted materials after a discussion of this problem. The balance of materials should be discussed rather than the number of materials.

2.1.4 Difficulty in Selection of Adjectives

As described thus far, some researchers used adjectives for the validates of extracted perceptual dimensions. Hence, there are difficulties related with the selection of effectual adjectives.

A limitation of lexicons is a problem. Although the macro and fine roughness were interpreted as separated dimensions in some studies, the adjectives representing macro and fine roughness such as “flat,” “smooth,” and “even” are semantically similar. Some researcher did not use these two types of adjectives. Guest et al. shown one comprehensive list of adjective words representing tactile perception or emotion [14].

Another problem is general disagreement for lexicons among participants. Soufflet et al. reported that the disagreement for lexicons result in a problem [46]. Women classified stimuli into smaller groups than men in their experiments. In addition, although the label “nervous” was frequently used by most of the workers in a textile industry to represent sensory aspects of stimuli, most of non experts did not use it.

2.2 Studies on Structuring Psychophysical Dimensions for Perceptual Spaces

The author searched the studies investigating the perceptual dimensions of tactile perception. The constructed dimensions, the used materials are shown in Table 2.2. The names of spaces in some studies were interpreted by adjectives, which may be different from the

Table 2.2 Reference table of studies on psychophysical spaces for internal tactile responses

Author	Year	Texture	Dimension 1	Dimension 2	Dimension 3	Dimension 4	Modality
Howorth [7]	1968	12 fabrics	Rough/smooth Hard/soft	Warm/cold			Haptic
Yoshida [8]	1968	25 materials	Hard/soft, Cold/warm, Rough/smooth	Wet/dry, Smooth/rough	Hard/soft		Visuo-hapt.
Lyne [40]	1984	8 tissues paper towels	Hard/soft	Embossed (Roughness)			Visuo-hapt.
Hollins [10]	1993	17 materials	Rough/smooth, Warm/cold, Sticky/slippery,	Hard/soft	Not specified (Stiff)		Haptic
Hollins [12]	2000	17 materials	Rough/smooth	Hard/soft	Sticky/slippery		Haptic
Picard [11]	2003	24 car seats	Hard/soft, Rough (Fine roughness)	Relief (Macro roughness)	Hard/soft		Haptic
Picard [45]	2004	40 fabrics	Hard/soft	Rough/smooth			Haptic
Soufflet [46]	2004	26 fabrics	Rough/smooth Hard/soft	Warm/cold			Haptic
Ballesteros [41, 43]	2005	20 materials	Rough/smooth	Hard/soft	Slippery/sticky		Haptic
Shirado [31]	2005	20 materials	Rough/smooth	Cold/warm	Moist/dry	Hard/soft	Haptic
Gescheider [47]	2005	7 raised dots	Macro roughness	Rough/smooth	Fine roughness		Unknown
Bergmann Tiest [42]	2006	124 materials	Hard/soft	Smooth/rough	Not named	Not named	Haptic
Tanaka [38]	2006	13 fabrics	Moist/dry, Rough/smooth	Hard/soft, Cold/warm			Haptic
Yoshioka [33]	2007	16 materials	Hard/soft	Rough/smooth	Sticky/slippery		Haptic
Summers [48]	2008	10 papers	Rough/smooth				Haptic
Guest [49]	2011	15 fluids	Slippery/sticky	Rough/smooth	Oily		Haptic
Guest [14]	2011	5 fabrics	Rough/smooth	Moist/dry	Hard/soft		Haptic

names in the original studies. The author qualitatively summarized the names by taking into account how they were discovered. The author summarizes some examples from the reviewed studies, which are described below.

Howorth 1958 (Roughness & warmness): Howorth and Oliver constructed the perceptual space of tactile properties for 12 samples [7]. In their experiment, 25 participants compared pairs of stimuli in terms of the qualities of smoothness, coarseness, softness, stiffness, warmth, firmness, thickness and weight, then subjective scores were calculated depending on ranks of comparison tests. The subjective scores were analyzed using a factor analysis, and then three dimension were extracted.

The first dimension for psychophysical responses was related to smoothness, coarseness, and softness based on factor loadings for subjective scores. The second dimension was correlated with subjective warmth. The other dimension was correlated with subjective scores for weight and did not show strong correlations with psychophysical perception, which is omitted from the list of psychophysical dimensions in Table 2.2.

Yoshida 1968 (Roughness, hardness, warmness & moistness): Yoshida constructed the perceptual dimensions of tactile properties for 25 materials including aluminum, vinyl, nylon, and linen using an SD method with 20 adjectives [8]. Twenty-five participants explored the materials with visual information. Compared with other studies, the participants were allowed to touch the stimuli freely. A factor analysis extracted four factors.

The first factor was related to the subjective scores of “hard-soft,” “cold-warm,” “rough-smooth,” and “painful-not painful.” The author omits “painful-not painful” from psychophysical properties of surfaces. The second factor was described by “wet-dry,” “smooth-rough,” and “heavy-light.” The author does not treat “heavy-light” as a psychophysical property of materials. Thus, this label was omitted from the list. The third factor was related to “sharp-dull.” The author does not consider that the “sharp-dull” label represent psychophysical properties of materials. The fourth factor was described by “elastic-not elastic.” The author assume that this label interpreted surface elasticities. Therefore, the author treated this factor as the “hard-soft” factor.

Lyne 1984 (Hardness & roughness): Lyne et al. investigated the structure of perceptual spaces for 8 tissues and paper towels [40]. They used a similarity estimation method and MDS. Forty participants evaluated the materials with visual and haptic information.

They investigated the relationships between extracted dimensions and physical properties of stimuli. As a result, the first factor was related to surface softness of the stimuli, thus the author treated this factor as a softness dimension. The second factor was related to bending stiffness of stimuli, thus the author omit this factor from perceptual dimensions of physical properties of surfaces. The third factor was described by embossed properties of stimuli. The author interpreted this factor as a roughness dimension.

Hollins 1993 and 2000 (Roughness, hardness & slipperiness): Hollins et al. constructed the perceptual dimensions for 17 materials using a classification method and MDS [10]. Twenty participants passively touched the materials where the material beneath a finger pad moved. As a result, three factors were extracted. The first factor was interpreted as the combination of roughness, warmness, and stickiness. The second factor was described by "hard-soft." The third factor was correlated with did not strongly correlated with any adjective scales representing the perception of physical properties of surfaces.

Later, Hollins et al. constructed the perceptual dimensions using a similarity estimation method and MDS [12]. Although the previous study in [10] focused on a general trend, this report focused on individual differences in extracted dimensions. The two- or three- dimensional spaces were constructed. The dimensionality differs depending on participants. Two-dimensional spaces were described by "rough-smooth" and "hard-soft" dimensions. Three-dimensional spaces were interpreted as "rough-smooth," "hard-soft," and "sticky-slippery."

Shirado 2005 (Roughness, warmness, moistness, & hardness): Shirado et al. constructed the perceptual dimensions for 20 materials such as wood, fabric, and metal using a SD method [31]. Thirty participants touched the materials without vision. Thirteen adjective and Japanese onomatopoeia label pairs such as *sara-sara/nuru-nuru* and *zara-zara/sube-sube* were used in their experiments. Using a factor analysis, they extracted the four factors which are interpreted as roughness, warmness, friction, and hardness dimensions, respectively, based on factor loadings.

Tanaka 2006 (Roughness, moistness, hardness, & warmness): Tanaka et al. investigated the perceptual spaces for 13 materials, including silk, satin, and cotton using a SD method and a factor analysis [38]. Twenty-one blindfolded participants joined the experiments and evaluated materials using seven adjective pairs. As a result, two dimensions were extracted. The first factor was represented by the combination of "rough-smooth" and "moist-dry." The second factor was interpreted by the combination of "hard-soft," "flat-downy," and "warm-cold." It is reasonable that "flat-downy" mostly represents "hard-soft" because the used stimuli were attached on flat panels.

Yoshioka 2007 (Roughness, hardness, & slipperiness): Yoshioka et al. constructed the perceptual dimensions for 16 materials using a similarity estimation method and MDS [33]. Eight participants joined the experiments. The extracted three dimensions were compared with the subjective ratings for adjectives. Accordingly, the these dimensions were interpreted as "rough/smooth," "hard/soft," and "sticky/slippery," respectively.

2.3 Common Dimensionality for Perceptual Responses: Five Psychophysical Spaces

A common dimensionality for perceptual responses to materials has not yet been found. In Sec. 2.2, the related studies were summarized that they adopted different combinations of experimental methods, analytical methods, set of materials, and adjectives. Here, the author constructs common dimensions for perceptual responses to surfaces calculating the number of reports of similar dimensions found in different studies. The calculated number of perceptual dimensions reported in related studies are shown in Table 2.3.

2.3.1 Three Fundamental Dimensions: Roughness, Hardness, and Warmness

The three types of dimensions such as roughness, warmness, and hardness dimensions were frequently extracted. The perceptual mechanisms of these three types of dimensions obviously differ, which are described in Sec. 2.4. The author reasonably captures these dimensions as the common dimensions for perceptual responses to surfaces.

In terms of the contribution of theses three dimensions in Table 2.3, the roughness or hardness dimensions were the most salient dimensions. Bensmaïa and Hollins found that roughness and friction more strongly influenced the perceptual dissimilarities between materials than warmness [50].

Dimensions of Macro and Fine Roughness

Some studies extracted the types of roughness such as macro and fine roughness, which were interpreted by the "uneven" or "relief" labels and the "rough" or "harsh" labels, respectively. Gescheider et al. separated the macro and fine roughness dimensions based on the difference in the adaption of Pacinian corpuscles [47]. Picard et al. extracted macro and fine roughness, which were referred to as relief and roughness, respectively in their study [11]. One reason to separate these two types of roughness is based on the perceptual mechanisms of these perception. The perceptual mechanisms of these two roughness are potentially different. Details are described in Sec. 2.4. This thesis considers that the fine and macro roughness perception pertain to different dimensions. However, the difference of perceptual mechanisms is not directly related to the difference of perceptual dimensions.

Table 2.3 Number of reports of perceptual dimensions in 16 studies

Rough/smooth		Hard/soft	Cold/warm	Frictional	
18		14	7	10	
Macro	Fine			Moist/dry	Slipp./sticky
2	2			5	5

Separately extracting the macro and fine roughness dimensions is difficult. The first reason is overlapped perceptual mechanisms of macro and fine roughness, which are explained in Sec. 2.4. The second reasons is that "rough" and "smooth" adjectives can describe both macro and fine roughness. The similar words to a "smooth" word are "even" or "flat" words. Using deficient adjectives will lead to confounding the macro roughness dimension with fine roughness dimensions. Gescheider et al. validated the consistency of adjectives by post hoc analyses [47].

2.3.2 Dimension of Friction

Dimensions of Moist/dry and Slippery/sticky

Dimensions interpreted by moist/dry [38, 31, 51, 49] and sticky/slippery [12, 33, 41, 49] were reported. Friction of surfaces may mediate these dimensions. The perception of sticky/slippery and moist/dry was related to frictional coefficients or frictional forces [52, 53, 33, 49]. In addition, the dimensions of moist/dry and slippery/sticky perception have never been extracted independently in a single study. The author reasonably conclude that the moist/dry and slippery/sticky dimensions come from the frictional dimension.

Relationships between Friction and Roughness Dimensions

A correlation between friction and roughness perception is reported [54, 21, 55]. However, lubrication of surfaces did not influence the perception of fine roughness for them [56]. In addition, the Perceived of roughness was influenced by the surface roughness rather than the friction between a finger and a surface [57]. The dimensions of surface roughness and friction may be different because many studies extracted the friction (sticky/slippery or moist/dry) dimension and the roughness (rough/smooth) dimension independently in a single study [51, 12, 31, 33, 41, 49].

The frictional dimension was sometimes covered by the roughness dimension because differences in surface roughness are partly affected by frictional properties of surfaces. Smith et al. reported that the relationships between tangential forces and perceived roughness using raised dots surfaces showed positive correlations when participants stroked their fingers down surfaces [21]. In addition, the number of materials that represent salient frictional properties was relatively small. Then, multivariate analyses might regard the frictional dimension as a minor dimension because of imbalanced materials.

2.3.3 Five Dimensions of Tactile Perception

The roughness, warmness, and hardness dimensions as shown in Fig. 2.1 were frequently extracted in the reviewed studies. This common structure of perceptual dimensions is agreed with the study on the categorization of perception. Tiest classified several types of perception into the four types of perception such as roughness, compliance, coldness and slipperiness [5]. Bensmaïa also reported these four types of perception [4]. This thesis underlies their categorization based on the trend of extracted dimensions of perceptual properties of surfaces.

The five types of perceptual dimensions described above have not yet been extracted in a single study. Although Hollins et al. used the five adjectives such as "rough/smooth," "flat/bumpy," "hard/soft," "slippery/sticky," and "warm/cool" to constrcut the dimensions, they extracted only two or three dimensions because they used the limited number of materials [10]. In addition, the perceptual dimensions of four physical properties such as spring constant, kinetic friction coefficient, bump size, and vibration were not separated in a subsequent study using virtual stimuli presented by a force feedback device [58]. Identifying the five dimensions in a single experiment is a task for future studies. Materials and adjectives that represent individual perceptual dimensions should be balanced.

2.4 Discussion: Differences of Perceptual Mechanisms

The author compendiously shows the perceptual mechanisms in order to underlie the separation of the five types of perceptual dimensions. Further details and a discussion on related controversial issues are included in the review articles by Jones and Lederman [59], Lederman and Klatzky [60], Bensmaïa [4], and Tiest [5].

2.4.1 Perceptual Mechanism of Roughness/smoothness

The perceived roughness is related with the fineness of surface roughness. Many researchers reported that the perceptual mechanisms of macro and fine roughness are different in the size of grating wavelengths. The author treated that the perception of roughness should be divided into the perception macro and fine roughness.

Macro and Fine Roughness

For the perception of macro roughness for a material, e.g. materials above grating wavelengths of 1 mm, humans tend to push their finger on the surface and the pressure distribution in contact are used. Neurophysiological studies explained that the spatial distribution of SAI units is related to roughness perception [61, 62, 63].

For the perception of fine roughness, the temporal information on skin vibration caused by stroking a finger on rough textures plays and important role [64, 20]. The contribution of the vibratory information for the micro roughness is clearer than that for micro roughness [65, 66]. These findings indicate that FAI and FAII units contribute to the perception of fine roughness.

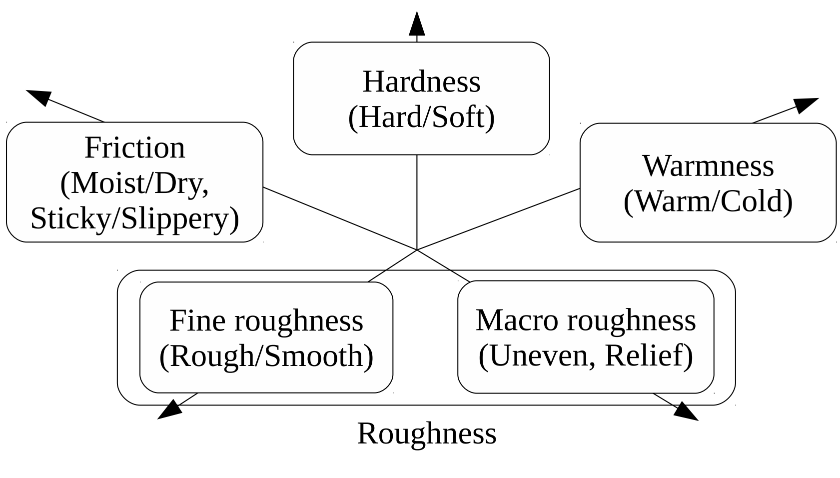

Fig.2.1 Five psychophysical spaces of internal tactile responses for materials

2.4.2 Perceptual Mechanism of Hardness/softness

Hardness perception tends to be treated as the perception of the spring constant of stimuli and be categorized into the perception of force. However, it is also mediated by the tactile information from finger skin [67, 68]. The contact area between a finger pad and a surface is related to the perception of hardness. In [69, 70], the researchers developed the tactile softness softness displays that controlled the the contact area between a finger pad and a contactor. Identifying a dominant information from the information in a contact area such as the pressure distribution in the contact area, the history of area changes, or another type of information is a task for future studies.

2.4.3 Perceptual Mechanism of Friction

The perception of softness or elasticity is attributable to tactile cues

Although friction perception tends to be treated as the perception of force, it is also mediated by information from finger pad skin. It is considered that the skin stretch or adhesion of a finger pad contributed to the perception of friction. It is reported that the perceived friction was affected by the stick-slip phenomenon between a finger pad and a stimuli [71, 72]. Zigler reported that the perception of stickiness and wetness was related to the adhesion of finger pad skin during stroking a surface [73, 74]. It is also demonstrated that the friction perception is correlated with the magnitude of the skin stretch of finger pad [75]. It is known that many types of receptors in finger pad skin could be activated by dynamic skin stretch caused by friction [76, 77].

One may doubt the difference between the perception of friction and fine roughness. However, some researchers reported the findings supporting the separation of the perception of friction and fine roughness. Taylor and Lederman demonstrated that the perception of roughness was insensible to the differences in frictional status of stimuli using lubricant soap [56]. Nonomura et al. examined the frictional perception of a flat stimuli with different frictional statuses using lubricant oils [71]. In their experiments, although finger pad skin did not vibrate, participants could estimate the magnitude of friction.

2.4.4 Perceptual Mechanism of Warmness/coldness

Heat transfer between finger skin and a surface is used for material recognition [78]. The perception of warmness/coldness is contributed by heat transfer properties between finger skin and a surface [27, 31, 79, 80, 81, 82]. Recently, it is reported that several types of transient receptor potential protein (TRP) ion-channels on free nerve endings in finger skin were identified as the receptors for warmness and coldness [83, 84]. These ion-channels are activated in different temperature bands. For example, TRPV1, TRPV2, and TRPA1 responds to stimuli above approximately 43°C, above approximately 52°C, and below approximately 17°C.

2.5 Summary of Chapter 2

This chapter focused on the dimensions of the perception of physical properties of materials. The author reviewed the studies on the construction of psychophysical dimensions. The psychological experiments for collecting of subjective data were restricted by an unsatisfactory adjectives, the number or balance of materials. In addition, analytical methods such as a factor analysis and a multidimensional scaling method never cover all dimensions.

The consistently-extracted three dimensions are represented as the roughness, warmness, and hardness dimensions. The roughness perception was separated into macro and fine roughness perception in a few studies. These two types of roughness perception can be interpreted as different dimensions because of the difference in the perceptual mechanisms of them. The dimensions described by moist/dry and sticky/slippery adjectives were extracted in many studies. The author summarized that these two types of dimensions should be treated as a single dimension because both perception are mediated by the friction of materials. The author reasonably concludes that the common dimensions of the perception of physical properties of materials are five types of dimensions such as macro roughness, micro roughness, warmness, hardness, and friction.

Chapter 3

Multilayered Model of Perceptual, Affective, and Hedonic Responses

This chapter constructed the construction methodology of a multilayered model of words representing internal responses of human as an example shown in Fig. 3.1.

A challenge exists in determining a structure for the multilayered model of internal responses. It is difficult to assume causal relationships between variables because information about the structure of combined variables does not exist. Causal relationships should in some way be obtained. To solve the difficulties in constructing a multilayered model, the author evaluated the causalities between adjectives representing internal responses.

The author proposed a computational method of a semantically multilayered model expressing internal responses, including two processes. For the first process, shown in Fig. 3.2a, the author evaluated causalities between adjectives based on the decision-making trial and evaluation laboratory (DEMATEL) method [85]. DEMATEL is typically used for the construction of relationships between variables on a social problem, which has not yet been applied to the study on human internal reactions. Reported causalities determine the structure of the model. For the second process, shown in Fig. 3.2b, undefined parameters in the structure built in the first process are statistically estimated using structural equation modeling [86]. The author then finally acquired a semantically multilayered model for tactile textures.

3.1 Experiment for Evaluating Construction Method of Multilayered Model of Human Internal Response

To validate the proposed method, the author conducted experiments and constructed a multilayered model of touch-related internal responses. The author performed experiments using 11 volunteers. The volunteers included seven males and four females, aged 19 to 23 years, with no history of deficits in tactile processing, including eight participants with corrected vision. All experimental procedures, including the recruitment of participants, were approved by the Ethics Committee of the Graduate School of Engineering at Nagoya University.

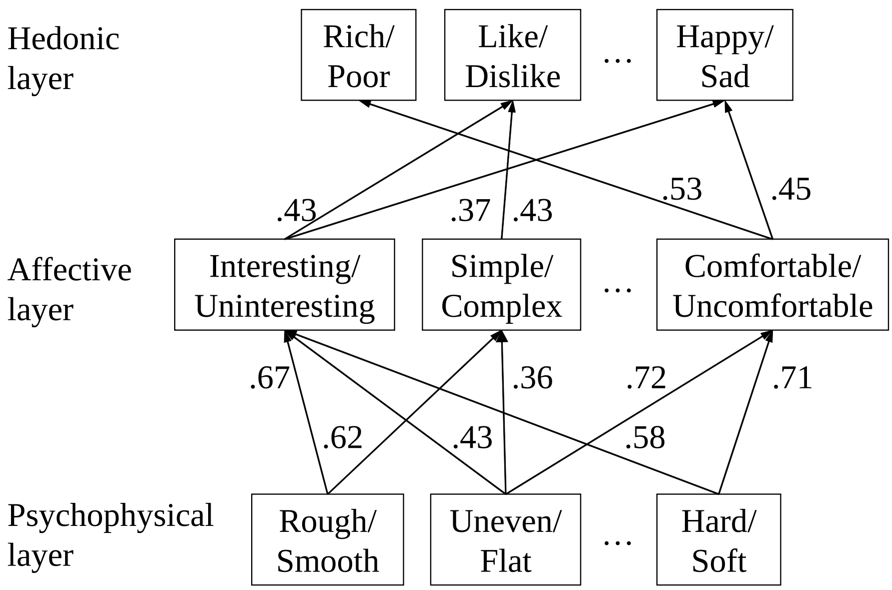

Fig.3.1 Concept of semantically layered model of tactile textures. Values represent magnitude of relationship between adjectives

3.1.1 Experimental Materials

Forty-six materials, shown in Table 3.1, were used in the experiments. To construct a general model of touch-related internal responses, a biased material set was avoided. A wide variety of materials were used, including wood, paper, fur, and fabric. The size of each material sample was 90 mm × 90 mm square, which was sufficiently large for participants to touch the sample with several types of touch motions, such as pushing and stroking. To prevent slippage of the material by touching, the material was attached to a flat plate with double-sided tape.

3.1.2 Adjective Pairs Representing Touch-related Internal Responses

Twenty-nine adjective pairs, shown in Table 3.2, were used to represent internal responses to touching materials. These adjectives were selected based on studies on dimensions for

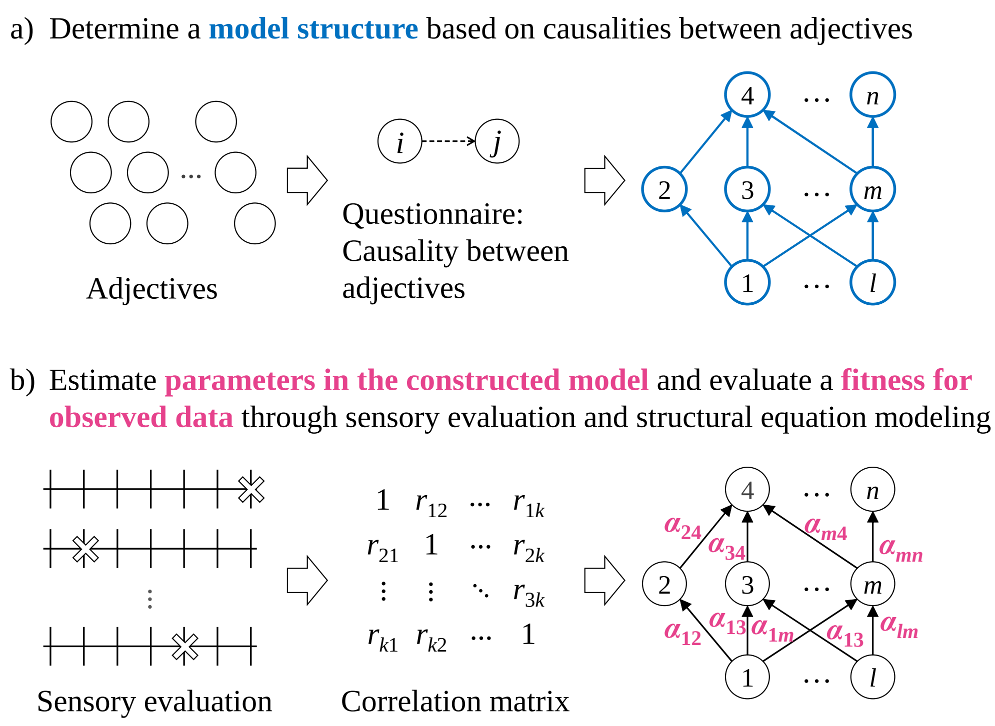

Fig.3.2 Construction process of layered model

tactile textures (e.g., [14, 7, 8, 10]) and included the five common adjectives representing the psychophysical percepts of tactile textures [13]. In addition, the list includes terms, such as "comfortable-uncomfortable" and "rich-poor," which were expected to be included in affective and hedonic layers and are potentially helpful in the manufacturing of commercial products.

3.1.3 Construction of Multilayered Structure Based on Causalities Between Adjectives

Evaluation of Causalities Between Adjectives

The 11 volunteers ($n = 11$) actively touched the 46 materials shown in Table 3.1, which were individually presented to each participant in a randomized order. The participants

Table 3.1 List of forty-six materials

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

were instructed to freely touch the materials in the box; they did not see the materials and their own touching motions. After touching all the materials, they evaluated causalities for all permutations of the adjective pairs: ${}_mP_2 = 812$, where m is the number of adjective pairs ($m = 29$). They scored causalities ${x_{ij}}^{(k)} (k = 1, 2, \ldots, n)$ in terms of the extent to which the subjective evaluation for all materials using adjective pair i influenced other evaluations using adjective pair j with a six-point scale ($5 =$ very influential; $0 =$ no influence).

Calculation of Total-relation Matrix

For each participant, an initial direct-relation matrix $\boldsymbol{X}^{(k)} \in \boldsymbol{N}^{m \times m}$ containing causalities ${x_{ij}}^{(k)}$ was normalized to $\boldsymbol{Z}^{(k)}$ as follows:

$$\boldsymbol{Z}^{(k)} = \frac{1}{s^{(k)}} \boldsymbol{X}^{(k)}, \tag{3.1}$$

Table 3.2 List of 29 adjective pairs used in the experiment

Beautiful-ugly	Like-dislike
Clean-dirty	Modern-classic
Clear-vague	Natural-artificial
Comfortable-uncomfortable	Regular-irregular
Concrete-abstract	Rich-poor
Dangerous-safe	Rough-smooth
Delicate-bold	Sharp-dull
Exciting-boring	Significant-insignificant
Friendly-unfriendly	Simple-complex
General-specific	Sticky-slippery
Good-bad	Strange-usual
Happy-sad	Uneven-flat
Hard-soft	Warm-cold
Interesting-uninteresting	Wet-dry
Itchy-not itchy	

where $s^{(k)}$ based on [85] was the maximal summation of rows or columns and was determined by

$$s^{(k)} = \max\left(\sum_{i=1}^{m} x_{ij}{}^{(k)}, \sum_{j=1}^{m} x_{ij}{}^{(k)}\right) \quad (i, j = 1, 2, \ldots, m). \tag{3.2}$$

Next, for construction of the structure based on general opinions, an average direct-relation matrix $\boldsymbol{A}$ was computed by all the participants as follows:

$$a_{ij} = \frac{1}{n}\sum_{k=1}^{n} z_{ij}{}^{(k)}. \tag{3.3}$$

where a_{ij} and $z_{ij}{}^{(k)}$ were elements of $\boldsymbol{A}$ and $\boldsymbol{Z}^{(k)}$, respectively. Finally, to account for both direct and indirect relations, the author computed total-relation matrix $\boldsymbol{F}$ as follows:

$$\boldsymbol{F} = \boldsymbol{A} + \boldsymbol{A}^2 + \boldsymbol{A}^3 + \cdots = \sum_{b=1}^{\infty} \boldsymbol{A}^b = \boldsymbol{A}(\boldsymbol{I} - \boldsymbol{A})^{-1} \tag{3.4}$$

where $\boldsymbol{A}^l$ is an indirect-relation matrix that indicates effects from adjective pairs i to j after mediating other (l-1) pairs.

Construction of Multilayered Structure Based on the Total-relation Matrix

Based on total-relation matrix $\boldsymbol{F}$, the structure of the multilayered model expressing the reported causal relationships between adjective pairs was determined. The structure consisted of nodes and arcs, which represented adjectives and presences of causal relationships between adjectives, respectively. When element f_{ij} of $\boldsymbol{F}$ was greater than a given threshold, a directional arc was set from adjective pairs i to j. When a threshold value was greater, the number of nodes and arcs would typically become greater, thereby resulting in a more complex structure. In addition, for clarification of characteristics of the structure, the number of arcs was minimized while maintaining reachability between nodes. For example, as shown in Fig. 3.3, the arc between nodes d and f was omitted when three arcs occurred across the three nodes d, e, and f.

The two types of structures, as shown in Figs. 3.4 and 3.5, were based on the two threshold levels: 0.047 and 0.039. In the figure, the line type represents the level of influence values estimated in Sec. 3.1.4.

3.1.4 Estimation of Parameters of Constructed Structure Based on Sensory Evaluation and Structural Equation Modeling

As outlined in Sec. 3.1.3, the structures were constructed based on causalities between adjectives. However, parameters in a structure, such as the magnitude of an influence between adjectives, covariance between ratings for adjectives, and error variances in ratings for adjectives, remained undefined. Thus, the author conducted a sensory evaluation and then statistically estimated model parameters using structural equation modeling.

Sensory Evaluation for Materials

The participants $(n = 11)$ evaluated the materials $(l = 46)$ by touching them and using a seven-point scale in terms of 29 bipolar adjective pairs $(m = 29)$, which resulted in evaluated values ${y_{ij}}^{(k)}(i = 1,2,\ldots,m, j = 1,2,\ldots,l, k = 1,2,\ldots,n)$. The author provided participants with an evaluation form, which included these terms in both English and Japanese. The materials and adjectives were respectively presented to the participants in a random order. The evaluated values were normalized to a mean of 0 and variance of 1 for each of the 46 adjectives; they were then averaged across all participant scores.

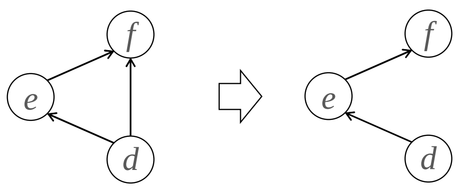

Fig.3.3 Rule of omitting arc while maintaining reachability

Estimation of Parameters Using Structural Equation Modeling

Structural equation modeling is a statistical method that compares a covariance structure represented by undefined parameters in a constructed model with a correlation matrix based on ratings on a sensory evaluation. It then estimates the undefined parameters in the structure. In this study, the author estimated the influence values between adjectives, error variances in ratings for adjectives, and covariances among the adjectives, which are enclosed with black dashed lines in Figs. 3.4 and 3.5.

Maximum likelihood estimation was used for the estimation of parameters. The likelihood function was defined as the product of the probability density function of the multivariate standard normal distribution. Parameters $\boldsymbol{\theta}$ in the constructed model were estimated as the maximum likelihood estimates $\hat{\boldsymbol{\theta}}$, which minimized the objective function determined by

$$f_{ML} = \mathrm{tr}(\boldsymbol{\Sigma}(\boldsymbol{\theta})^{-1}\boldsymbol{S}) - \log|\boldsymbol{\Sigma}(\boldsymbol{\theta})^{-1}|, \tag{3.5}$$

where $\boldsymbol{S} \in \boldsymbol{R}^{m\times m}$ and $\Sigma(\boldsymbol{\theta})$ represent the correlation matrix based on the ratings on the sensory evaluation and covariance structure represented by non-estimated parameters in the model as determined in Sec. 3.1.3.

3.2 Results: Multilayered Model of Adjectives Representing Psychophysical, Emotional, and Preferential Responses

The constructed multi-layered models are shown in Figs. 3.4 and 3.5. The estimated values of relations between adjectives, which were statistically estimated as not 0 ($p < 0.05$), are shown in Tables 3.3 and 3.4. The arcs in Figs. 3.4 and 3.5 correspond to the estimated values shown in Tables 3.3 and 3.4. To focus on influential arcs, nodes, and parameters, the other ones in the constructed models were omitted from the figures and tables.

The simple model in Fig. 3.4 includes 21 nodes and 38 arcs, while 23 nodes and 47 arcs in the complex model are shown in Fig. 3.5. Thus, the models showed different complexities in terms of layered structure.

Similarities were found in the models shown in Figs. 3.4 and 3.5. In both models, the lowest layer contained the six types of adjective pairs: "rough/smooth," "uneven/flat," "hard/soft," "cold/warm," "sticky/slippery," and "wet/dry." While these pairs relate to the psychophysical perception of materials, the higher layers tended to include the adjectives representing material attributes and affective responses. In addition, the four types of adjectives—"rich/poor," "good/bad," "happy/sad," and "like/dislike"—in the highest layer were significantly linked to individual preferences. It is reasonable to say that the lowest, middle, and highest layers respectively denoted psychophysical, affective, and hedonic layers. The constructed models corresponded to semantic multilayered relationships between adjective words, which demonstrated the availability of proposed method.

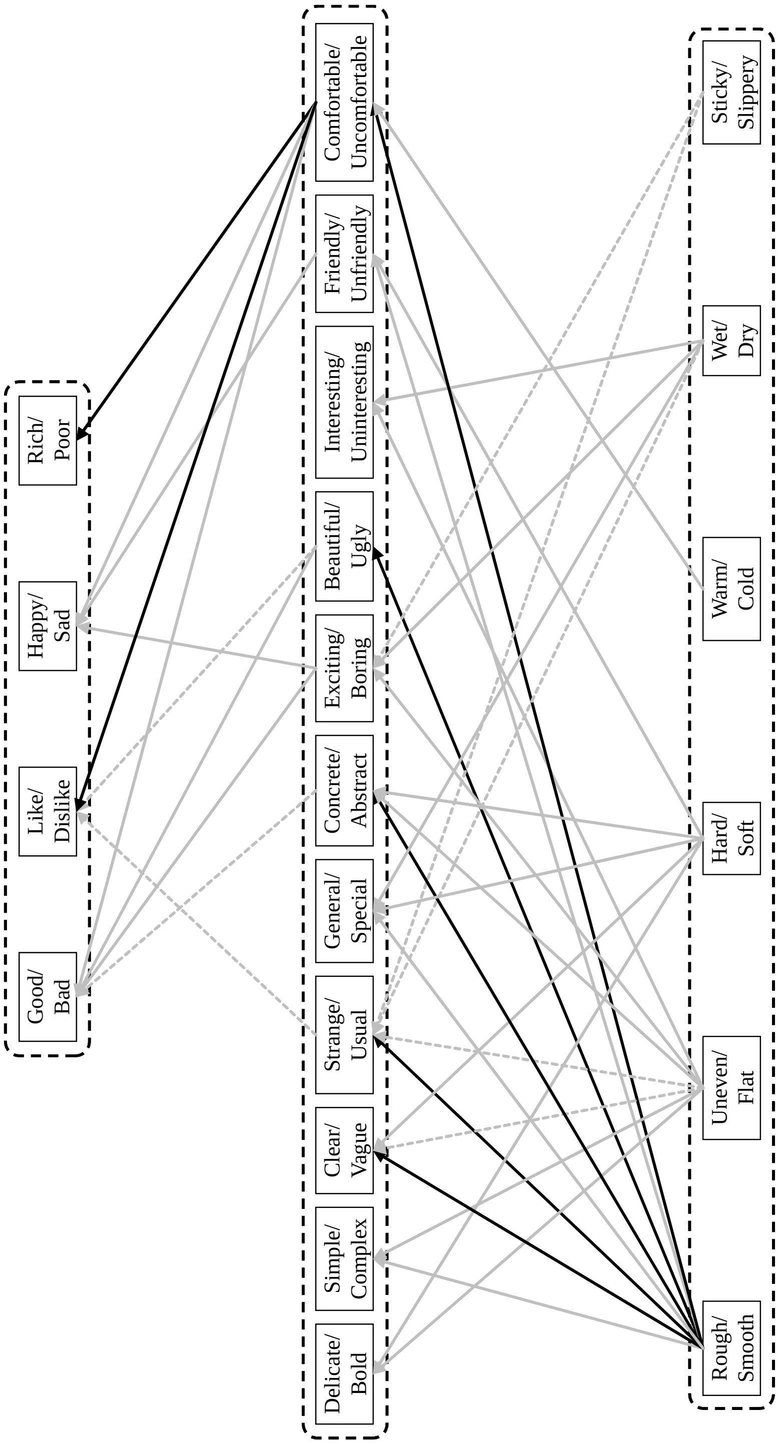

Fig.3.4 Example of simple model (threshold is 0.047). Black solid, gray solid, and gray dashed lines represent the causal relationships with the magnitude of estimated influence values 0.6 and over, from 0.3 to 0.6, and under 0.3, respectively.

Table 3.3 Estimated values of influence between adjectives in the simple model shown in Fig. 3.4

	Delicate/ Bold	Simple/ Complex	Clear/ Vague	Strange/ Usual	General/ Special	Concrete/ Abstract	Exciting/ Boring	Beautiful/ Ugly	Interesting/ Uninteresting	Friendly/ Unfriendly	Comfortable/ Uncomfortable	Good/ Bad	Like/ Dislike	Happy/ Sad	Rich/ Poor
Rough/ Smooth		-0.48	-0.81	0.75	-0.35	-0.77		-0.73		-0.36	-0.67				
Uneven/ Flat	-0.33	-0.48	0.21	0.17		0.55	0.51		0.50						
Hard/ Soft	-0.33		0.52		-0.30	0.59				-0.38					
Warm/ Cold											0.32				
Wet/ Dry				0.23	-0.37		0.37		0.46						
Sticky/ Slippery				-0.13			0.23								
Strange/ Usual													-0.27		
Concrete/ Abstract												-0.17			
Exciting/ Boring												0.30		0.30	
Beautiful/ Ugly												0.33	-0.21		
Friendly/ Unfriendly														0.56	
Comfortable/ Uncomfortable												0.51	0.85	0.45	0.84

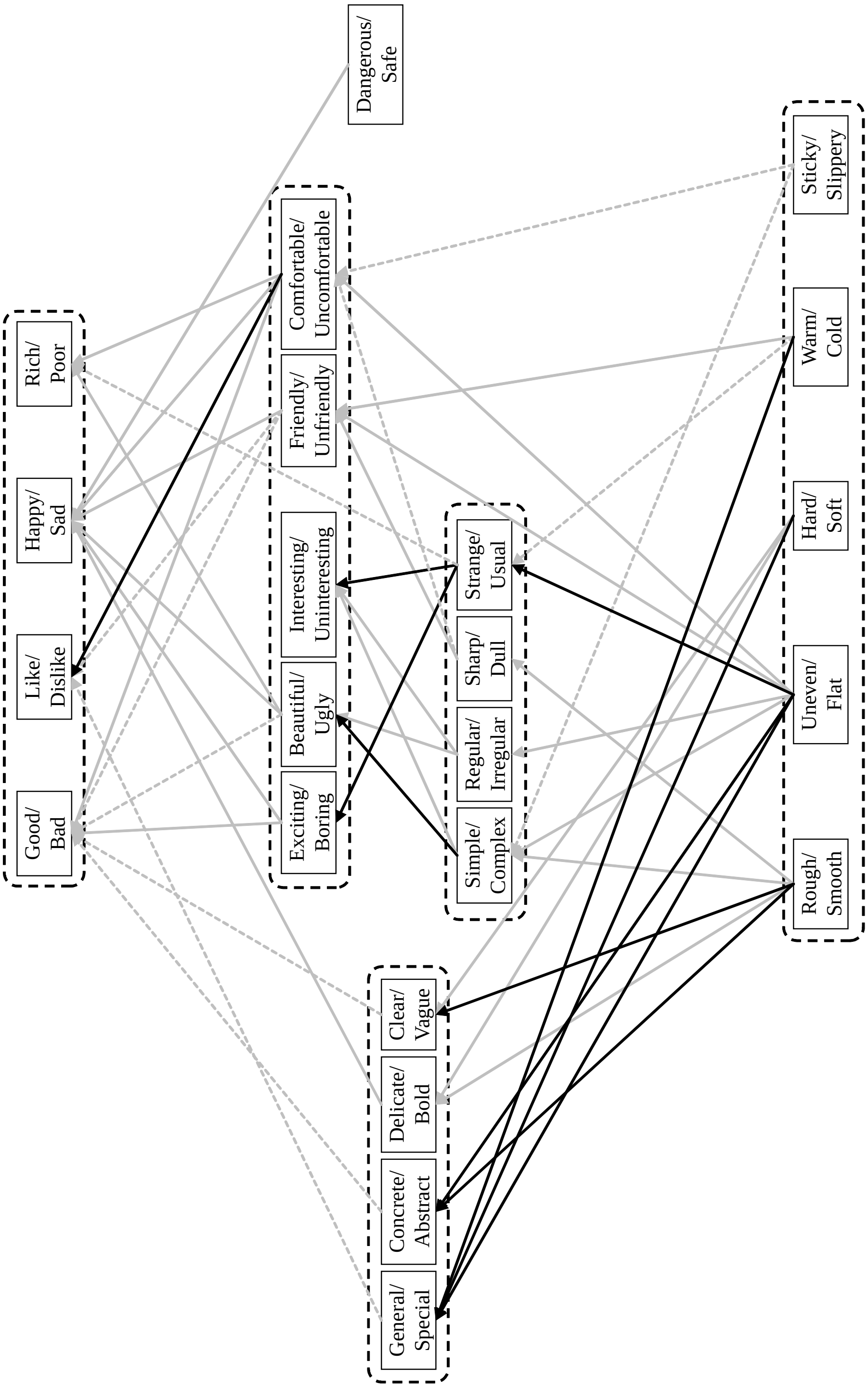

Fig.3.5 Example of complex model (threshold is 0.039)

3.3 Discussions

3.3.1 Discussion 2: Validation of Proposed Method Based on Constructed Models

Quantitative Validity

To quantitatively validate the proposed method, the author calculated the fit indices demonstrating the extent to which a constructed model represents the results of the sensory eval-

Table 3.4 Estimated values of influences between adjectives in the complex model shown in Fig. 3.5 (Part 1)

	Simple/ Complex	Regular/ Irregular	Sharp/ Dull	Strange/ Usual	General/ Special	Concrete/ Abstract	Delicate/ Bold	Clear/ Vague	Exciting/ Boring	Beautiful/ Ugly	Interesting/ Uninteresting	Friendly/ Unfriendly	Comfortable/ Uncomfortable
Rough/ Smooth	-0.47		-0.46			-0.66		-0.85					
Uneven/ Flat	-0.57	-0.48		0.60	-0.79	0.59						-0.33	-0.33
Hard/ Soft					0.67		-0.53	0.42					
Warm/ Cold				-0.27	1.04							0.43	
Sticky/ Slippery	0.11												-0.27
Simple/ Complex										0.65	0.33		
Regular/ Irregular										-0.32	-0.34		
Sharp/ Dull												-0.43	-0.18
Strange/ Usual									0.75		0.64		

uation. The goodness-of-fit index (GFI) is described by

$$\mathrm{GFI} = 1 - \frac{\mathrm{tr}((\boldsymbol{\Sigma}(\hat{\boldsymbol{\theta}})^{-1}(\boldsymbol{S} - \boldsymbol{\Sigma}(\hat{\boldsymbol{\theta}})))^2)}{\mathrm{tr}((\boldsymbol{\Sigma}(\hat{\boldsymbol{\theta}})^{-1}\boldsymbol{S})^2)}, \tag{3.6}$$

while the comparative fit index (CFI), which considers the degree of freedom of the model, is described by

$$\mathrm{CFI} = 1 - \frac{\max((l-1)f - d_f, 0)}{(l-1)f_0 - d_{f0}}, \tag{3.7}$$

where l, f, d_f, f_0, and d_{f0} are the number of materials $(l = 46)$, the maximum likelihood value and the degree of freedom in the constructed model, respectively; i.e., those in an independent model with no relation between adjectives. GFI and CFI were values from

Table 3.5 Estimated values of influences between adjectives in the complex model shown in Fig. 3.5 (Part 2)

	Good/ Bad	Like/ Dislike	Happy/ Sad	Rich/ Poor
Strange/ Usual				0.25
General/ Specific		-0.13		
Concrete/ Abstract	-0.21			
Delicate/ Bold			0.20	
Clear/ Vague	0.20			
Exciting/ Boring	0.37		0.33	
Beautiful/ Ugly	0.21		-0.18	0.54
Friendly/ Unfriendly	0.18	0.25	0.56	
Comfortable/ Uncomfortable	0.44	0.68	0.43	0.49
Dangerous/ Safe			0.16	

0 to 1; a greater value signified that the constructed model better explained the observed data.

The relationships between the six types of threshold values (0.35, 0.39, 0.43, 0.47, 0.51, and 0.55) and the values of the GFI and CFI indices in the constructed models are shown in Fig. 3.6. The simple model (threshold = 0.47) in Fig. 3.4 had the largest GFI (0.73) and CFI (0.93) among the six models; therefore, the model was quantitatively validated in terms of model fitness. In this study, when a threshold greater than 0.47 was used, the model's structure was simplified; accordingly, the numbers of nodes and arcs were small (e.g., the constructed model based on the threshold value of 0.55 had two featureless layers), which resulted in a decrease of fitness. On the other hand, when the threshold was smaller than 0.47, the fitness likewise decreased because of an increase in the number of adjectives that scarcely aligned with the observed data. The user can accept the model quantitatively validated on the basis of the model fitness.

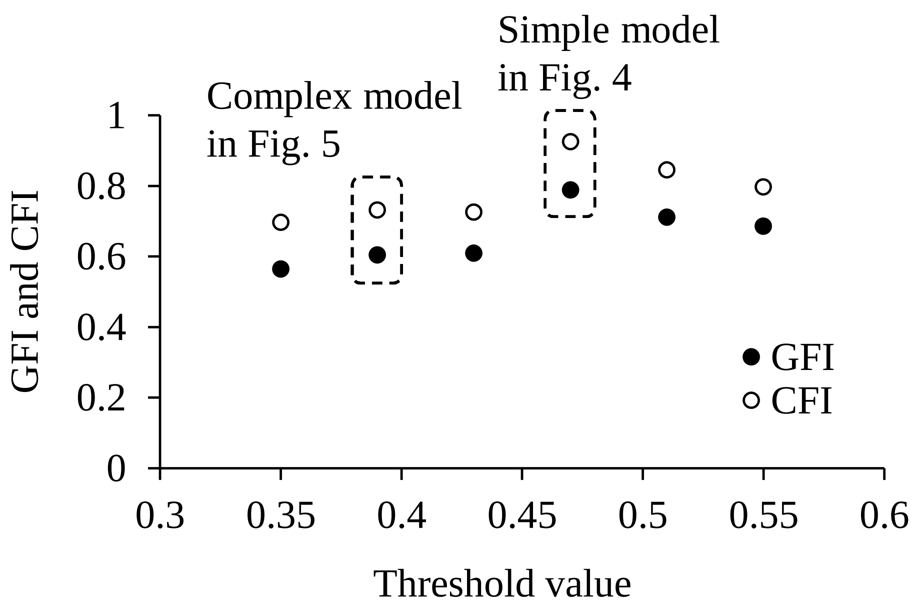

Fig.3.6 Relationships between GFI and CFI and threshold values

Semantic Validity

For discussion of the semantic validity of the proposed method, the author compared the multilayered models in this study with models in related studies on multilayered spaces of tactile textures. Here, the constructed models were comprised of the three types of layers: psychophysical, affective, and hedonic. Similar characteristics were found in the related models.

The model in the study by Chen et al. [28], for example, is comprised of psychophysical and affective layers in which psychophysical words influence affective ones. This arrangement of layers is partly consistent with that of the present study. In terms of the psychophysical layer, although they handle "rough-smooth" and "uneven-flat" as one subjective roughness, the composed adjectives in the two studies are very similar. Their model includes sub-middle layers; a similar structure with sub-middle layers is found in the present study ' s complex model shown in Fig. 3.5. In addition, in both studies, "exciting" is placed in higher layers, whereas "simple" is situated in lower layers. Moreover, Chen et al. did not use preferential or hedonic words, such as "rich-poor," "good-bad," "happy-sad," and "like-dislike," which comprise the hedonic layers in this study.

Guest et al. [14] investigated the dimensionality of the psychophysical layer representing sensory attributes of human internal responses and the affective layer representing emotional attributes. They demonstrated that the principal dimensions in the psychophysical layer are "rough-smooth," "dry-wet," and "hot-cold," which are included in the lowest layers in the models of this study. The major adjectives in the affective layer of their study are "comfort-discomfort" and "low-high arousal" (i.e., according to "exciting-calming" or "relaxing"). Such a trend is likewise observed in the present study.

The similarities between the models based on the proposed method and those of other studies [28, 14] support the validity of the constructed models in the present study and semantically validate the proposed method.

3.3.2 Discussion 2: Guidance and Limitations of Proposed Method

A user of the proposed computational method must consider some limitations when constructing a multilayered model of internal responses. First, it is necessary to apply materials and adjectives before constructing the model. If a user wants to construct a model for a certain type of material, such as clothing fabric or car upholstery, material that suits the given purpose must be used. In addition, the adjectives that a user would like to integrate in the model should be used. The number of adjectives relates to the number of trials in evaluating causalities, which increases the burden on participants. Therefore, experiments with a redundant number of adjectives should not be performed.

Next, threshold values must be determined. The complexity of the model structure, based on the number of nodes, arcs, and layers, is changed by the threshold value. A model based on a greater threshold will become a simple one containing fewer nodes and arcs, which is suited to easily understanding a model of internal responses. On the other hand, for a detailed analysis or an application to product design, a complex model based on a greater threshold value may be better. In addition, as shown in Fig. 3.6, the model fitness will also be changed according to the threshold value. Thus, in determining the structure of a model, its fitness for handling observed data should also be considered.

3.4 Summary of Chapter 3

This chapter presented a computational method of a semantically multilayered model that expresses human internal responses to touching materials. The proposed method is comprised of two processes consisting of the structure construction and estimation of parameters in the structure. In constructing the model structure, the correlated relationships between ratings assigned to descriptive words are unsuitable, whereas the causal relations between them are desirable. Therefore, by applying the DEMATEL method, causalities between adjectives can be evaluated for construction of the model structure. Sensory evaluation is then conducted followed by structural equation modeling. This results in the statistical estimation of undefined parameters in the constructed model, including influence values between adjectives.

To validate the proposed method, the author conducted experiments and constructed models to represent the relationships between touch-related internal responses. The two models that the author constructed are comprised of three types of layers that include adjectives respectively representing psychophysical, affective, and hedonic responses. This indicates that the proposed method is applicable to constructing a semantically multi-layered model of internal human responses. In the proposed method, the threshold value determines the complexity of the model structure. Thus, using several types of thresholds, the author constructed the models with different numbers of nodes and arcs; the fit indices were then calculated for the sensory evaluation data of each model. For the material set in this study, one constructed model demonstrated good performance (CFI $= 0.93$) in representing the observed data. The proposed method of connecting perceptual, emotional, and preferential words that express touch-related internal responses will help in the estimation of various impressions on product design and in the analysis of human percepts.

Chapter 4

Perceptual Responses and Physical Properties that Affect the Degree of Haptic Invitation

This chapter constructed the model describing the relationships among visual and sensory factors for materials and degree of haptic invitation as an example shown in Fig. 4.1, which demonstrates the factors of materials that invite human touch and what extent the linear connection of these factors can describe degree of haptic invitation.

Through a experiment with an abundant number of participants with the approval of local ethics committee, the author investigates how and to what extent the visual and sensory factors of textures correlate with the degree of haptic invitation and the extent to which the linear connection of these factors can describe the degree of haptic invitation. The author uses materials that allow us to control the four visual factors (physical properties of materials) and conducts sensory evaluations and a factor analysis to obtain the sensory factors (perceptual responses for materials). Multiple regression analyses reveal that how and to what extent the physical and sensory factors of materials explained the degrees of haptic invitation, respectively. Furthermore, the author investigates the effects of surface colors on the degree of haptic invitation in detail with Experiment 2.

In experiments, participants evaluate textures without touching them because textures' visual appearances contribute to their appeal to human touch. If the participants touch textures, their experiences could affect the affinity. Also, “touch” does not imply pushing, or holding an object; it simply implies stroking the surface of textures.

The degree of haptic invitation may depend on personal predispositions of participants, however, the large portion of such degree is considered to be common when their cultural background or generation is similar. The author averages individual responses to investigate a general trend in the relationships between the properties of textures and the degree of haptic invitation. Participants are limited to university students around 20 years of age. In order to impede the variations in cultural background from affecting the intensity of haptic invitation, the textures used in experiments should not be associated

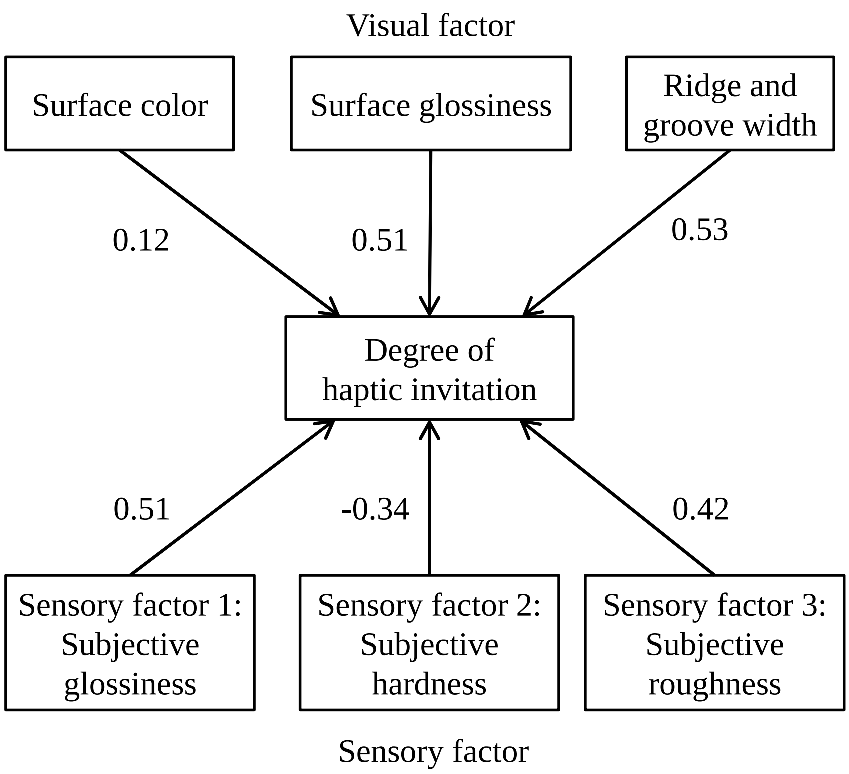

Fig.4.1 Concept of the model representing the relationships among sensory factors (internal responses), visual factors (physical properties) of materials and degree of haptic invitation. Values represent magnitude of relationship between variables

with something specific. For example, the people who prefer a small mammal may feel inclined to touch a smooth animal fur. The author uses simple clay plates with textured surfaces, which will not be affected by cultural background well.

4.1 Experiment for Specifying Perceptual Responses and Physical Properties that Affect Degree of Haptic Invitation

In Experiment 1, through two tasks, the author specified the sensory properties of textures and degree of haptic invitation. In Task 1, the participants evaluated textures one after the other using a semantic differential (SD) method. The author then applied factor analysis to acquired data to obtain independent sensory factors. In Task 2, the participants ranked all textures in order of the intensity of their degree of haptic invitation for materials. Based on the ranks of the materials, the author calculated the degrees of haptic invitation for each texture. Finally, the author investigated the relationships between the degrees of haptic invitation and the visual and sensory factors using multiple regression analyses. The experiments and procedures including the recruit of participants were approved by the local ethical committee in Nagoya University.

4.1.1 Experimental Materials

Ideally, the author should investigate the influence of as many visual factors as possible. However, due to practical limits, the author prepared 24 stimuli that were controlled by four visual factors: surface color, gloss pattern, surface shape type, and surface ridge and groove width. The author adopted light clay (Hearty Soft White, PADICO; Tokyo, Japan) as surface material of stimuli. The clay was molded into 55.0 mm $\times$ 55.0 mm $\times$ 5.0 mm flat plates using aluminum frame pairs. The surface color was either blue or orange; the clay was mixed with paint before molding. The color variation of blue and orange is a complementary relationship in the Munsell color system. These colors were expected to cause a larger variation in sensory evaluations. The blue (Phthalocyanine Blue, Liquitex; Ohio, USA) and orange (Scarlet Red, Liquitex; Ohio, USA) paints were (4.0BP, 1.5, 7), and (8.0R, 5.0, 13), respectively, in the Munsell color presentation. The mixing ratio was 100 g clay to 1.25 ml paint. Glossy and glossless textures were prepared. To make the textures glossy, the plates were varnished (SEALER Super Gloss, PADICO; Tokyo, Japan) after being colored, molded, and dried. The JIS specular gloss values of the textures were 2.4% and 94.2% for the glossless and glossy blue respectively; they were 1.7% and 85.1% for the glossless and glossy orange, respectively. As shown in Fig. 4.2, the author used two shapes, gridded and striped. The groove and ridge widths were 0.5, 1.0, or 2.0 mm. In total, 24 types of textures were prepared (2 colors $\times$ 2 gloss patterns $\times$ 2 shape types $\times$ 3 ridge and groove widths). The examples of used textures are shown in Fig. 4.3.

The visual factors of the textures were quantified by visual factor scores. The visual factor scores were normalized to a mean of 0 and a variance of 1 for each of the four factors: surface color (1, blue; -1, orange), gloss (1, glossless; -1, glossy), shape type (1, stripe; -1, grid), and ridge and groove width (-1.07, 0.5 mm; -0.27, 1.0 mm; 1.34, 2.0 mm).

4.1.2 Experiment 1: Evaluation of Perceptual Responses to Material

Method: Sensory Evaluation

In order to quantify the sensory properties of textures, the author conducted sensory evaluations using an SD method. Participants evaluated the textures using five-point scales in terms of adjective pairs, such as "rough-smooth." The adjective pairs used in the experiments were chosen in accordance with studies on visual and haptic perception [8, 9, 10, 12, 11, 31, 38]. The author provided both English and Japanese terms on the evaluation sheets. The author conducted preliminary experiments to remove and merge the candidate adjective pairs according to their appropriateness for the stimuli in this study. For example, the author removed the terms whose scores did not vary, such as "thick-thin." In addition, the author merged adjective pairs with similar meanings such as “shiny-matte” and “glossy-dull.” This process led to the final 16 adjective pairs shown in Table 4.1. The adjective pairs also included “predictable-unpredictable” to quantify texture predictability. This point is described in detail in Sec. 4.3.1.

Sixteen university students approximately 20 years of age volunteered to participate. As shown in Fig. 4.2b, a large white plate with a 50 mm × 50 mm square window was placed on a sample so that the participants would see only the textured surfaces and not the sides of the samples. The participants were instructed to keep their head positions fixed in order to retain the relative position between the head and samples. The textures and adjective pairs were presented to each participant in random order.

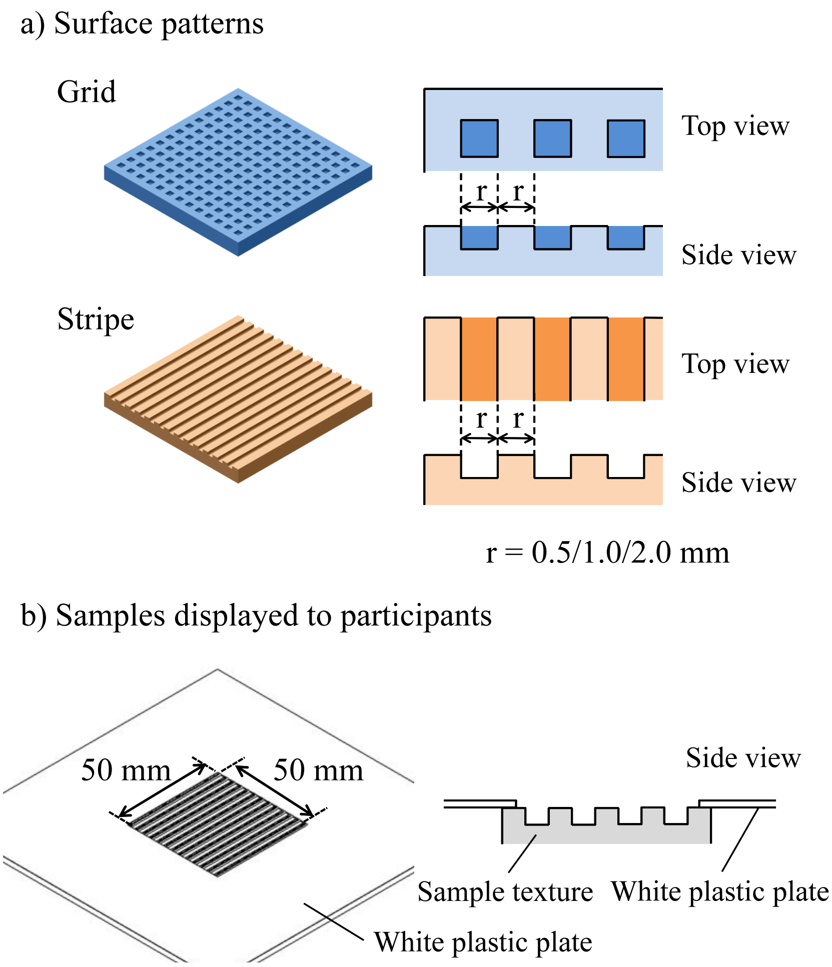

Fig.4.2 Clay sample textures

The author conducted experiments during between July 14th and August 9th in 2011. The laboratory temperature and humidity were approximately 28 °C and 65%, respectively. The textures were placed under an illumination of approximately 700 lx.

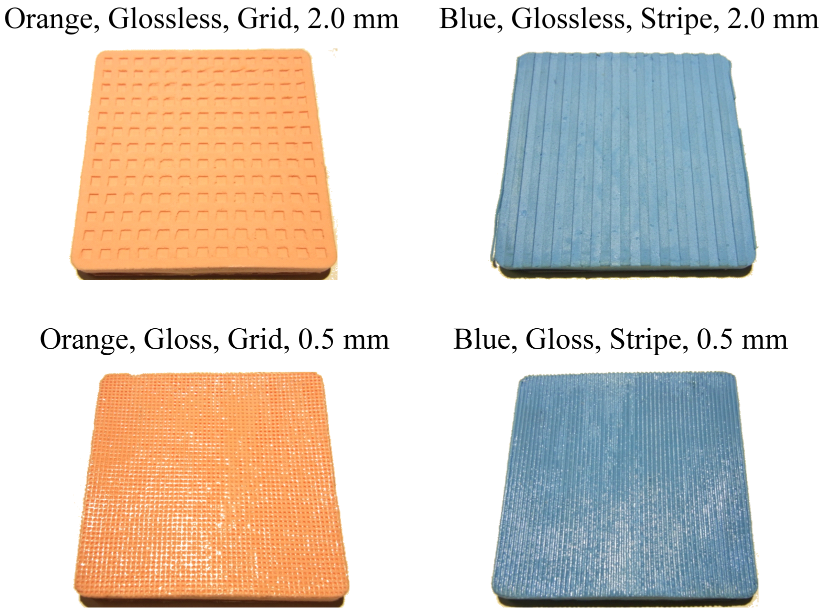

Fig.4.3 Used Stimuli (Surface Color, Gloss Pattern, Shape Type, Ridge and Groove Width)

Table 4.1 List of sixteen adjective pairs used in the experiment

Comfortable-uncomfortable	Sharp-blunt
Dark-light	Simple-complex
Dry-wet	Slippery-sticky
Elegant-inelegant	Soft-hard
Glossy-glossless	Uneven-flat
Harsh-not harsh	Vague-clear
Predictable-unpredictable	Vivid-colorless
Rough-smooth	Warm-cold

Data Analysis: Factor Analysis

The author assigned values of 1 to 5 to the five-point adjective scales obtained in Task 1. The evaluated values of each adjective pairs were normalized within a single participant, and were then averaged across all the participants. To decrease the number of variables used in later analyses, the author applied factor analysis to the values and extracted common factors as a synthesis of variables that were strongly correlated. $\boldsymbol{x}_i$ was the vector of evaluation values of p adjective pairs for the texture specified by i. The adjective pairs were those listed in Table 4.1 excluding "predictable-unpredictable"; thus, $p = 15$. $\boldsymbol{x}_i$ was broken down into m common factor scores $\boldsymbol{f}_i$ and unique factor scores $\boldsymbol{e}_i$:

$$\underset{p\times 1}{\boldsymbol{x}_i} = \underset{p\times m}{\boldsymbol{A}}\underset{m\times 1}{\boldsymbol{f}_i} + \underset{p\times 1}{\boldsymbol{e}_i} \quad (i = 1, \cdots, n), \tag{4.1}$$

where the factor loadings $\boldsymbol{A}$ explain the strength of relationships between common factors and adjective pairs. n was the number of samples ($n = 24$). In this model, the correlation matrix $\boldsymbol{R}$ of x can be represented as

$$\underset{p\times p}{\boldsymbol{R}} = \underset{p\times m}{\boldsymbol{A}}\underset{m\times p}{\boldsymbol{A}^{\mathsf{T}}} + \underset{p\times p}{\boldsymbol{D}} \tag{4.2}$$

where $\boldsymbol{D} = diag({d_1}^2, \cdots, {d_p}^2)$ are unique factors. Matrix $\boldsymbol{R}^*$, where diagonal elements of the correlation matrix $\boldsymbol{R}$ are replaced by the estimated communality ${h_j}^2$, is

$$\boldsymbol{R}^* = \begin{bmatrix} {h_1}^2 & r_{12} & \ldots & r_{1p} \\ r_{21} & {h_2}^2 & \ldots & r_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ r_{p1} & r_{p2} & \ldots & {h_p}^2 \end{bmatrix} (= \boldsymbol{R} - \boldsymbol{D}). \tag{4.3}$$

$\boldsymbol{R}^*$ is approximated by

$$\boldsymbol{R}^* = \hat{\boldsymbol{A}}\hat{\boldsymbol{A}}^{\mathsf{T}} \tag{4.4}$$

where $\hat{\boldsymbol{A}}$ is the approximation of $\boldsymbol{A}$. $\hat{\boldsymbol{A}}$ is given by $\boldsymbol{R}^*$'s m largest eigenvalues $\hat{\lambda}_1, \cdots, \hat{\lambda}_m$ and their corresponding eigenvectors $\hat{\boldsymbol{c}}_1, \cdots, \hat{\boldsymbol{c}}_m$. $\hat{\boldsymbol{A}}$ is

$$\hat{\boldsymbol{A}} = \left[\sqrt{\hat{\lambda}_1}\hat{\boldsymbol{c}}_1, \cdots, \sqrt{\hat{\lambda}_m}\hat{\boldsymbol{c}}_m \right]. \tag{4.5}$$

The author extracted the potential factors that explain textures by applying factor analysis to 15 adjective pairs excluding "predictable-unpredictable." The author applied varimax rotation to the factor loadings $\hat{\boldsymbol{A}}$ to facilitate interpretation of the relationships between factors and adjective pairs.

Results: Factor Loadings of 15 Adjective Pairs

The factor loadings and each factor's cumulative contributing rates are shown in Table 4.2. A cumulative contributing rate is a percentage that represents the degree to which the variation of adjective scores given to textures is described by the obtained factors. The author adopted a four-factor model ($m = 4$) because the cumulative contributing rate was nearly saturated with $m = 4$. Cells with absolute factor loadings of 0.7 or above are highlighted in gray. Because the adjective pairs with large factor loadings represent the property of the factor, the author named Factor 1 as the "dry factor," Factor 2 as the "uneven factor," Factor 3 as the "cold factor," and Factor 4 as the "simple factor." Factor 1 was affected by the fineness of the surface, which was associated with dryness, glossiness, and slipperiness. In contrast, Factor 2 was affected by the macro roughness of the surface. As indicated in Table 4.2, the cumulative contributing rate of the four factors was approximately 0.82. Thus, the dimensional space of the texture sensations was well established.

Experiment 2: Evaluation of Degrees of Haptic Invitation for Materials

The degree of haptic invitation for materials has not been substantially investigated; thus, methods to measure it have not been established. The author focuses on the fact that, although it is difficult to quantify the degrees of haptic invitation for participants using visual analog scales or magnitude estimation methods, participants can confidently judge which material is the most frequently invite human touch among several materials. Accordingly, the author introduced a ranking method which allows the participants to rank materials in the order of the intensity of the degree of haptic invitation. The author then exploit a normalized-rank approach [87] to convert the ranks to interval scales. In this approach, stimuli should be randomly chosen. Only stimuli that are either highly likely or highly unlikely to attract human touch should deliberately not be adopted. Such deliberate selection of stimuli creates an imbalances in the stimuli population. In this study, the au-

Table 4.2 Results of factor analysis: Factor loadings of 15 adjective pairs

	Factor 1	Factor 2	Factor 3	Factor 4
Glossy	−0.918	−0.276	−0.068	−0.266
Dry	0.916	0.114	−0.135	0.289
Harsh	0.839	0.243	0.215	−0.006
Slippery	−0.726	−0.598	−0.122	−0.158
Uneven	0.115	0.861	−0.047	0.306
Rough	0.407	0.756	0.179	0.097
Soft	0.187	0.726	−0.241	0.165
Dark	0.235	−0.023	0.969	−0.034
Cold	−0.336	−0.111	0.891	0.037
Vivid	−0.423	0.026	−0.845	0.044
Simple	0.020	0.291	0.025	0.862
Comfortable	0.434	−0.094	−0.082	0.667
Elegant	0.405	−0.331	−0.538	0.483
Sharp	−0.021	−0.611	−0.018	0.349
Vague	−0.339	−0.543	0.029	−0.615
Contribut. rates	0.263	0.215	0.195	0.149
Cumulative Contribut. rates	0.263	0.478	0.673	0.822
Featuring name	Dry fac.	Uneven fac.	Cold fac.	Simple fac.

thor exhaustively crossed four physical factors to produce texture stimuli. The normalized rank approach should be applicable to the texture stimuli of this study. A paired comparison method is another method of estimating the magnitude of haptic invitation. However, the paired comparison method requires a large number of trials to ensure reliability.

Method: Ranking 24 Materials

Twenty-four samples were simultaneously presented to each participant. The participants ranked the textures in terms of the degree of haptic invitation for the stimuli. Each participant was allowed to give the same rank to different stimuli if s/he was unable to rank all of the stimuli without duplicating ranks. Presenting all 24 materials to the participants at once allowed them to evaluate the relative differences in the textures. In order to avoid order effects, eight participants performed Task 1 first followed by Task 2 while the other eight participants performed Task 2 first followed by Task 1.

Data Analysis: Normalized-rank Approach

The author converted the ranks of the textures to interval scales using the normalized-rank approach [87]. The author defined these interval scales as the degrees of haptic invitation for the stimuli. The degree of the kth ranked texture was assigned to the expected value of the kth largest observation in samples of size n from a standard normal population. The degree of the kth ranked texture was determined by

$$E(x_{k|n}) = \frac{n!}{(n-k)!(k-1)!} \int_{-\infty}^{\infty} x \cdot a(x) \cdot b(x) \cdot \phi(x) dx \tag{4.6}$$

$$a(x) = \left[\tfrac{1}{2} - \Phi(x)\right]^{k-1} \tag{4.7}$$

$$b(x) = \left[\tfrac{1}{2} + \Phi(x)\right]^{n-k} \tag{4.8}$$

$$\phi(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\tfrac{1}{2}x^2\right) \tag{4.9}$$

$$\Phi(x) = \int_0^x \phi(z) dz. \tag{4.10}$$

The degrees of haptic invitation for a certain texture were averaged across the participants.

Results: Degrees of Haptic Invitation for 24 materials

Fig. 4.4 shows the degrees of haptic invitation that resulted from Task 2. The error bars indicate the standard deviations among the participants. The stimuli are arranged in descending order of degree. In terms of the surface gloss, the degree of haptic invitation for glossless textures was higher than that for glossy textures. The majority of the textures with high degrees of haptic invitation were glossless textures. Surface gloss was considered to affect the degree of haptic invitation more significantly than other physical factors. For shape type, the degree of haptic invitation for striped textures was higher than those for gridded textures. The glossless and striped textures showed higher degrees of haptic invitation.

4.1.3 Relationships Between Degrees of Haptic Invitation and Factors of Materials

To investigate the relationships between the degrees of haptic invitation for stimuli and factors of stimuli, the author performed a multiple regression analysis. This analysis connected the degrees of haptic invitation and the visual factors of textures as well as the degrees of haptic invitation and the sensory factors of the textures. The analysis was applied to the standardized values. In addition, the author obtained the correlation coefficients between the visual and sensory factor scores.

Relationships Between Degrees of Haptic Invitation and Visual Factors

The author conducted multiple regression analysis with the objective and explanatory variables being the degrees of haptic invitation and the visual factor scores of textures, respectively; the adjusted R^2 was 0.68. The standard partial regression coefficients are shown in Table 4.3.

The author performed t-tests to see whether the standard partial regression coefficients were significantly different from zero. A significant negative correlation between the surface gloss and degrees was observed (two-tailed t-test, $t(19) = 5.29$, $p = 4.14 \times 10^{-5}$). In

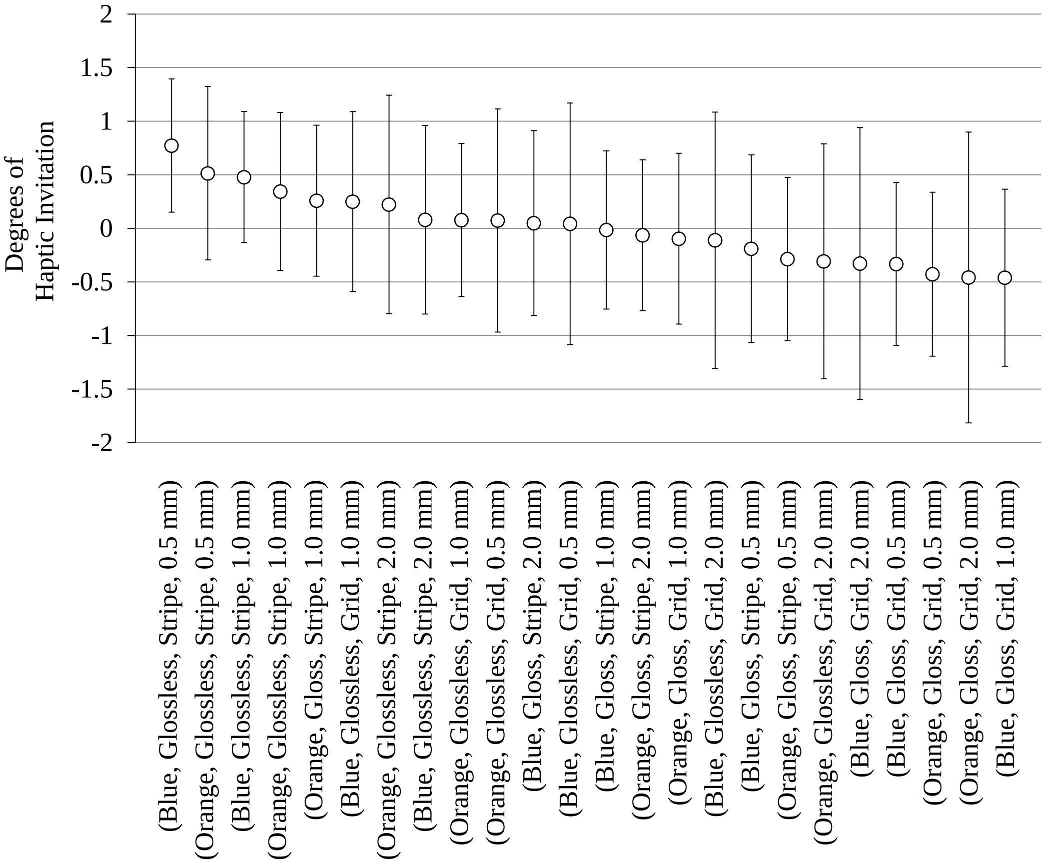

Fig.4.4 Degrees of haptic invitation for twenty-four materials

Table 4.3 Regression coefficients of visual factor scores and degrees of haptic invitation

	Color (+:Blue/ -:Orange)	Gloss (+:Glossless/ -:Glossy)	Shape Type (+:Stripe/ -:Grid)	Ridge and groove wid.
Regression coefficients	0.049	0.609***	0.540***	−0.207

other words, glossiness decreased the degrees of haptic invitation. One possible explanation of this result is that the majority of participants were disinclined to touch glossy textures because they are often associated with slimy surfaces. There also was a significant correlation between the shape type (stripe/grid) of the textures and degrees (two-tailed t-test, $t(19) = 4.69$, $p = 1.59 \times 10^{-4}$): the degrees for striped stimuli were greater than those for grid ones. Participants may have expected stronger tactile stimuli for the striped textures than for gridded ones. This is consistent with the observation that the majority of participants reported that they would touch the striped textures such that their fingers moved perpendicularly to the groove orientation. In such a case, their perceived roughness for striped textures would be larger than that for the gridded ones. Thus, the author speculates that a moderately intense tactile stimulus appeals to human touch. Ridge and groove widths (0.5/1.0/2.0 mm) did not impact the degrees of haptic invitation (two-tailed t-test, $t(19) = 1.80$, $p = 0.09$). Similarly, surface colors (blue/orange) also failed to impact the degrees of haptic invitation (two-tailed t-test, $t(19) = 0.43$, $p = 0.67$).

According to these analyses, the degrees of haptic invitation for glossless and striped textures should have high values. This estimate is consistent with the results shown in Fig. 4.4. The textures with the four largest degrees of haptic invitation were glossless and striped textures, whereas, the textures with the five smallest degrees of haptic invitation were glossy and gridded textures.

The present effects of surface roughness on degree of haptic invitation differ from previous findings [26] that showed that smooth stimuli invited human touch more than bumpy ones. However, in our study, ridge and grove widths did not impact the degree of haptic invitation. In addition, it appears that participants expected stronger tactile stimuli for the striped textures than the gridded ones, with affinity for the striped textures higher than that for gridded textures. The author speculates that this is due to differences in touching methods. In [26], touch possibly represented grasping whereas in our study, touch meant stroking. Consequently participants in [26] may have regarded surface roughness as an impediment to grasping.

Relationships Between Degrees of Haptic invitation and Sensory Factors

The author describes the relationships between the degrees of haptic invitation and sensory factor scores of stimuli ($\boldsymbol{f}_i$) that resulted from the factor analysis. The author conducted a multiple regression analysis with degrees of haptic invitation as the objective variable and the texture sensory factor score as the explanatory variable, yielding an adjusted R^2 of 0.75. Table 4.4 lists the resulting standard partial regression coefficients. Significant effects of the dry (two-tailed t-test, $t(19) = 4.48$, $p = 2.56 \times 10^{-4}$) and simple (two-tailed t-test, $t(19) = 6.93$, $p = 1.33 \times 10^{-6}$) factors on the degree of haptic invitation for materials were found. The relationship between the uneven factor and the degree of haptic invitation was not significant (two-tailed t-test, $t(19) = -1.45$, $p = 0.16$). The cold factor was also not significant (two-tailed t-test, $t(19) = 0.04$, $p = 0.97$). Thus, textures with dry and simple factors showed higher degrees of haptic invitation. Interestingly, though Factor 2 (uneven) was the second factor contributing to texture recognition, it did not contribute to degrees of haptic invitation. In contrast, Factor 4 (simple) was a minor factor for texture recognition but strongly influenced the degree of haptic invitation.

Correlations Between Visual and Sensory Factors

The correlations between the visual and sensory factors are presented in Table 4.5. Factor 1 (dry) was related to the surface gloss. Glossy textures had high Factor 1 values.

Table 4.4 Regression coefficients of sensory factor scores and degrees of haptic invitation

	Factor 1 Glossless Dry Harsh	Factor 2 Uneven Rough Soft	Factor 3 Cold Dark	Factor 4 Simple
Regression coefficients	0.476^{***}	-0.159	0.004	0.773^{***}

Factor 2 (uneven) was influenced by ridge and groove widths, indicating that coarser surface patterns were perceived as more uneven. The correlation between Factor 3 (cold) and surface color was strong. Finally, Factor 4 (simple) was affected by the shape type, with striped textures more likely to be perceived as simple than gridded textures.

Fig. 4.5 shows these relationships between the degrees of haptic invitation and the visual and sensory factors for materials. The line width represents relationship strength and corresponds to the absolute values in Tables 4.3, 4.4, and 4.5. Although these results are limited to the sample textures used in this study, the relationships between the degrees of haptic invitation and the visual and sensory factors of stimuli are nonetheless effectively quantified.

The author found that the visual and sensory factors effectively captured 68% and 75% of the variance of the degree of haptic invitation, respectively. The results support the argument that the degree of haptic invitation for material is generally determined by visual and sensory factors when properties of materials are limited. The remaining 20–30% of the variance that these factors could not describe may be due to the visual and sensory aspects of materials that were omitted in this study. Individual differences in decision criteria in the two experimental tasks may also have contributed to the residuals of the regression analyses.

Table 4.5 Correlation coefficients between visual and sensory factor scores

	Factor 1	Factor 2	Factor 3	Factor 4
Color	−0.066	−0.004	0.956	0.086
Gloss	0.913	0.276	0.033	0.301
Shape type	−0.183	−0.096	−0.062	0.807
R & G width	−0.296	0.771	−0.040	0.201

Attractiveness to Touch Comes from Comfort

The author used the adjective term pair "comfortable-uncomfortable" in Task 1. Thus, the author adopt the ratings for this pair as the index representing apparent comfort. This adjective pair does not represent the properties of any of the four sensory factors, nor does it describe tactile dimensions. However, the correlation coefficient between the degrees of haptic invitation for stimuli and the ratings for the "comfortable-uncomfortable" pair was approximately 0.82. Thus, a texture's apparent comfort potentially affects its attrac-

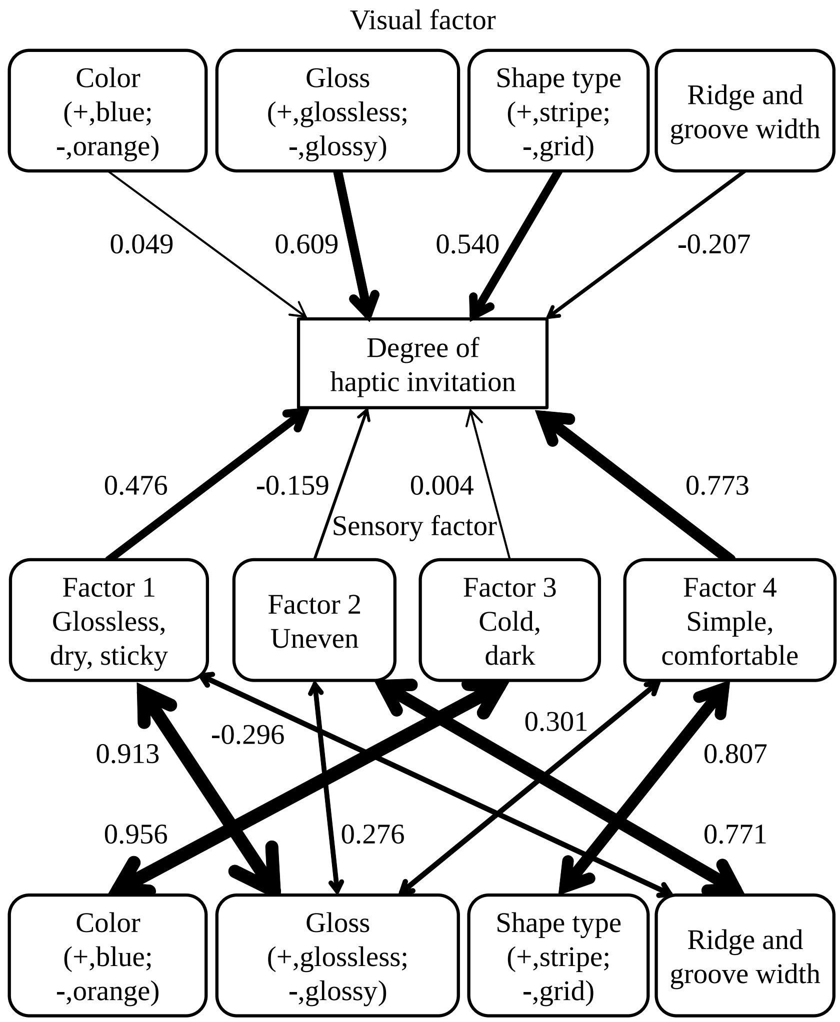

Fig.4.5 Relationships between sensory factors, visual factors of textures, and degrees of haptic invitation

tiveness to human touch, consistent with the result from Klatzky et al. [26]. Their index for attractiveness consisted of probing response to “touching this object would feel good” which appears to be similar to the “comfortable-uncomfortable” pair used in the present study.

4.2 Experiment for Investigation of Relationships Between Surface Colors and Degree of Haptic Invitation

The surface color of textures is potentially related to the degree of haptic invitation because colors are known to influence human sensations including preferences [88, 89, 90, 91]. However, there was little correlation between the degrees of haptic invitation and the surface colors (blue/orange) in Experiment 1. The color variation was too limited to conclude that surface colors hardly influence the degree of haptic invitation for materials. Thus, the author increased the number of surface colors and found out whether the surface color affected the affinity to textures in Experiment 2.

4.2.1 Measurement of Degree of Haptic Invitation for Five-colored Textures

The participants ranked the stimuli differing from ones used in Experiment 1 in order of the intensity of the degree of haptic invitation for them. The author used 10 different stimuli (5 colors $\times$ 2 ridge and groove widths). Each surface color was one of the five colors: blue, orange, purple, green and yellow. The blue, orange paints were the same as ones used in Experiment 1. The purple (Dioxazine Purple, Liquitex, Ohio, USA), green (Permanent Green Light, Liquitex, Ohio, USA) and yellow (Yellow Medium Azo, Liquitex, Ohio, USA) paints were (5.6P, 1.5, 1), (1.2G, 4.9, 10) and (3.7Y, 8.2, 13), respectively, in the Munsell color presentation. The Munsell color system has five primary hues (Red, Yellow, Green, Blue, Purple) that are equally perceptually spaced. Surface colors were determined by reference to these five principle colors. This color variation potentially causes a large variation in the degrees of haptic invitation for stimuli. The mixing ratio was the same as that in Experiment 1. All textures were glossless and striped textures. The groove and ridge widths were 1.0, or 2.0 mm. The author used the normalized-rank approach to convert the ranks to the degrees of haptic invitation for stimuli as the author did so in Experiment 1.

4.2.2 Results: Degrees of Haptic Invitation for Ten Material

The degrees of haptic invitation resulted from Experiment 2 are shown in Fig. 4.6. The textures are arranged in descending order of degree. The author performed a two-way ANOVA with explanatory variables of surface colors and ridge and groove widths and objective variables of the degrees of haptic invitation for stimuli. The result indicated insignificant effects of the surface color (two-way ANOVA, $F(4,150) = 1.15$, $p = 0.34$) and ridge and groove widths (two-way ANOVA, $F(1,150) = 0.82$, $p = 0.37$) on the degree of haptic inivitation. The effect sizes, as measured by partial η^2, were 0.030 and 0.005 for the surface color and ridge and groove width, respectively; they were equally low. The effect of surface color on the degree of haptic invitation was negligible as well as that of the ridge and groove widths.

4.3 Discussions

4.3.1 Discussion 1: Two Models Describing the Relationships Between Predictability of Properties and Degree of Haptic Invitation for Materials

The predictability of textures which indicates how predictable the tactile sensations of textures are from their appearances is potentially related to the degree of haptic invitation on any suggestive result in Sec. 4.1.2. For example, some people may want to touch textures whose haptic sensations are apparently unpredictable. On the other hand, others may not be interested in such textures. Thus, the author assumes that the predictability of textures affects the degree of haptic invitation for stimuli in certain manners.

Here, the author investigated how the predictability of textures related to the degree of haptic invitation for them. The author proposed the following two models that potentially described the relationships between the predictability and degrees of haptic invitation. The participants evaluated the predictability using five-point scales polarized by a "predictable-unpredictable" pair in Task 1 without touching them. Through multiple regression analyses, the author verified whether the models including predictability described degree of haptic invitation to textures better than the model in Sec. 4.1.3 did.

First Model: Predictability of Properties Affects Each of Sensory Factors

In the first model, the unpredictable textures minimally affect the degree of haptic invitation to textures, whereas the sensory factors of predictable textures strongly affect the degrees of haptic invitation. In other words, a texture that looks good or is predicted good induces human touch, whereas a texture that does not look good does not induce human

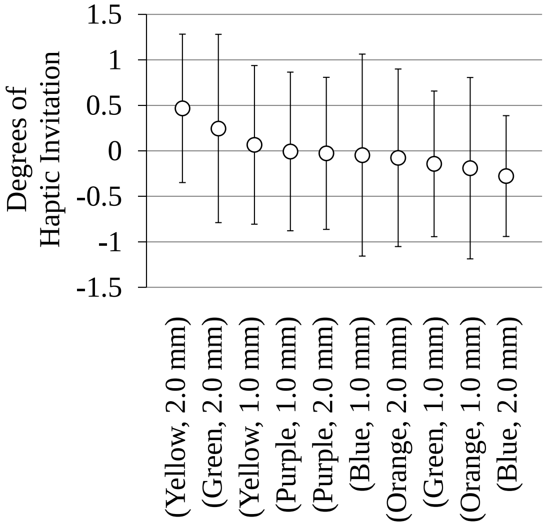

Fig.4.6 Degrees of haptic invitation for ten materials: 5 different surface colors

touch. Unpredictable textures tend to come in the moderate ranks of haptic invitation. The first model is

$$\widehat{a_k} = c_1 p_k f_{1k} + c_2 p_k f_{2k} + \cdots + c_4 p_k f_{4k}, \tag{4.11}$$

where $\widehat{a_k}$, c_j, p_k, f_{jk} were the estimated degree of haptic invitation, the standard regression coefficient, the predictability of textures, and the score of factor j for a texture specified by k, respectively. For p_k, the author assigned values of 1.0 to 0.2 on the five-point adjective scales obtained in Task 1 (1.0 = predictable, 0.2 = unpredictable) with a step of 0.2. In (4.11), the author multiplied p_k and each of the four sensory factor scores of textures f_{jk}. The degrees of affinity to unpredictable textures were reduced almost to zero to counteract the influence of the sensory factor scores on the degrees of haptic invitation. An adjusted R^2 of the multiple regression analysis of (4.11) was 0.74. This was as large as that of the model in Sec. 4.1.3 which was 0.75. The author expected adjusted R^2 of the model specified in (4.11) to be higher than that of the model in Sec. 4.1.3, but (4.11) described the degrees of haptic invitation as well as the model without predictability in Sec. 4.1.3 did. As an example of the causes, the model described by (4.11) did not properly account for the textures whose haptic sensations were unpredictable, but its degrees of haptic invitation was significant.

Second Model: Predictability of Properties is a Factor Independent on Sensory Factors

In the second model, the author considers linear relationships between the predictability of textures and degrees of haptic invitation for stimuli. This model describes the "predictable textures with high affinity" or "unpredictable textures with high degree of haptic invitation." The second model is

$$\widehat{a'_k} = c'_1 f'_{1k} + c'_2 f'_{2k} + \cdots + c'_4 f'_{4k} + c'_5 p'_k, \tag{4.12}$$

where predictability of textures p'_k affects the degrees of haptic invitation for stimuli as a factor independent on the four sensory factors of the textures. p'_k was different from p_k

in the first model, but represented normalized values in common with other explanatory variables f'_{jk}. Thus, p'_k values of the predictable textures were high, and p'_k of the unpredictable textures were low or negative. If c'_5 is positive, the more predictable textures show the higher degrees of haptic invitation. If c'_5 is negative, the degrees of haptic invitation to unpredictable textures are high, meaning that people would like to touch the textures in order to investigate their unpredictable haptic properties. The author verified the validity of this model through a multiple regression analysis. An adjusted R^2 was 0.74. The model in (4.12) described the degrees of haptic invitation as well as the model without predictability in Sec. 4.1.3 did; R^2 for the model in Sec. 4.1.3 was 0.75. Fig. 4.7 shows the results of the analysis. Values in the figure are the standard regression coefficients of the four factors and predictability. The coefficient between Factor 5 and the degrees of haptic invitation was positive, however, the correlation was not significant (two-tailed paired t-test, $t(18) = 0.81$, $p = 0.42$).

In summary, both the first and second models involving the predictability did not describe the degree of haptic invitation significantly better than the model without the predictability in Sec. 4.1.3. However, intuitively considering, predictability contributes to the affinity to human touch. The more sophisticated models potentially exist and remains as future works.

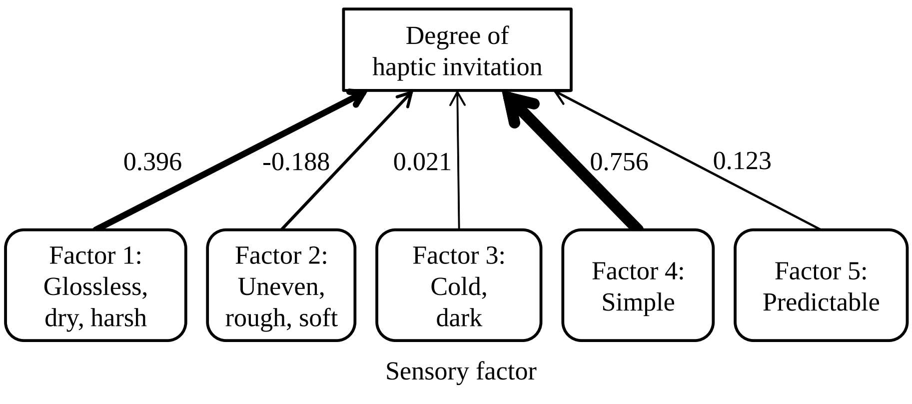

Fig.4.7 Relationships between factors including predictability and degrees of haptic invitation (Second model)

4.3.2 Discussion 2: Individual Differences in Degree of Haptic Invitation for Materials

The standard deviations of degrees of haptic invitation for textures were not small in Sec. 4.1.2, though the author pursued the general trends of affinity by using simple textures such that the effects of personal cultural background on the degree of haptic invitation was limited. In order to investigate the individual differences in the degrees of haptic invitation, the author clustered 16 participants by the degrees of haptic invitation using factor analysis. The author applied factor analysis to the degrees of haptic invitation for textures and located the participants in a two-dimensional space (Fig. 4.8). The author classified participants into 3 groups (A, B and C) based on the distribution of participants in two-dimensions, where group C was the major group and groups A and B were minor groups. Most of the participants had small values in Dimension 1, and the author categorized these participants as group C. The participants in group A exhibited high degree of haptic invitation for stimuli whose ridge and groove width were small. On a certain participant in group A, the correlation coefficient between the ridge and groove width and degrees of haptic invitation was -0.886. On the other hand, regarding the participants in group B, the degrees of haptic invitation for uneven materials were high. For example, the correlation coefficient was 0.786 on a certain participant in group B. The participants in group C narrowly distributed in Dimension 1, on the other hand, widely distributed in Dimension 2. Therefore, the author divided group C into groups C_1 and C_2. In group C_1, the degrees of haptic invitation for glossless materials were high. On a certain participant in group C_1, the correlation coefficient between the gloss pattern and degrees of haptic invitation was -0.672. On the other hand, the participants preferred to glossy textures in group C_2. For example, the correlation coefficient was 0.616 on a certain participant in group C_2. The majority of participants belonged to group C_1, however, some variations in the degree of haptic invitation were observed. Although this study focused on a general trend, individual differences should be properly considered in the future study.

4.3.3 Discussion 3: Effects of Surface Colors on Degree of Haptic Invitation for Materials

The statistical result of this study suggests that there is little influence of surface colors on degree of haptic invitation for materials. On the other hand, many effects of colors on human feelings have been reported. In terms of the effect of color on apparent thermal sensation, some reports agree with the followings. The colors with long-wavelength such as red, yellow, and orange are apparently warmer than the colors with short-wavelength such as violet, blue, and green [92, 93]. There are some relationships between the brightness of color and apparent weight [94, 95], and apparent size [96]. In addition, it is known that the color preference exists [88, 89, 90]. For example, colors with larger saturation and brightness are preferred in general [91].

The colors affected the human perceptions and preferences as mentioned above. The result of our research that the surface color hardly affected the degree of haptic invitation

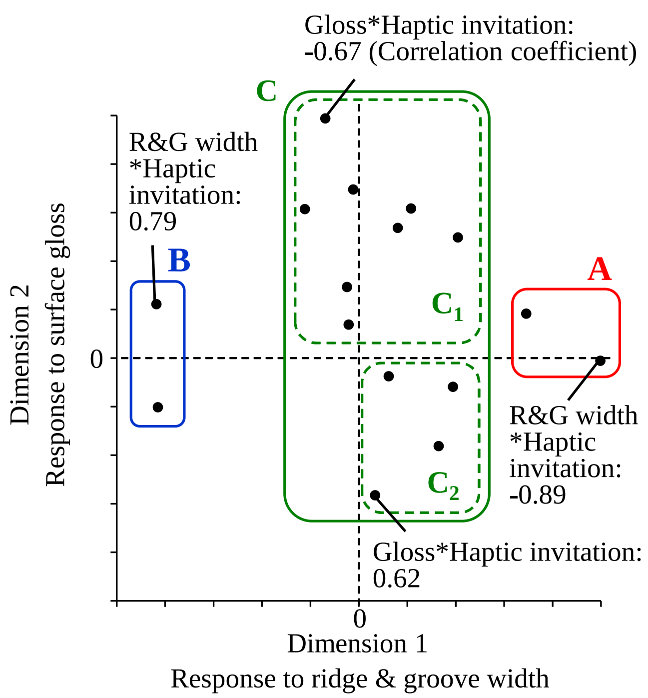

Fig.4.8 Distribution of 16 participants in two dimensions

did not follow this trend. One possible explanation is that the surface color does not originally affect the degree of haptic invitation, or the surface color of textures which not be associated with something specific does not affect the degree of haptic invitation. Another possibility is that the motivation of touch to textures is essentially different from the human perceptions or preferences for textures. One interesting fact was observed in our informal trial. The participants were confused a lot or were virtually impossible to perform a task when they were asked to rank textures in the order of preference. They require some criteria for judgment, such as preference as wall paper or carpet in their offices or houses. On the other hand, when they were asked to rank the textures in the order of affinity to textures, they could easily perform the task. This indicates that there is an inherent difference between texture preference and degree of haptic invitation.

4.4 Summary of Chapter 4

The author investigated the visual and sensory factors of materials that appeal to human touch. The author used stimuli in such a way that the author was able to control their four visual factors as surface color, gloss, shape type, ridge-groove width. In order to obtain the sensory factors of the stimuli, the author conducted sensory evaluations and factor analysis. Consequently, the four sensory factors were identified as dry, uneven, cold and simple factors, respectively. The degrees of haptic invitation were measured by a ranking system and the normalized-rank approach. Regarding the visual factors of textures, their glossiness and surface shape types strongly affected the degrees of haptic invitation. There was no correlation between their surface colors and the degree of haptic invitation for materials through further experimentation. Regarding the influence of sensory factors, dry and simple factors were observed to be strongly related to the degree of haptic invitation. Multiple regression analyses revealed that the visual and sensory factors effectively described the degrees of haptic invitation with accuracies of 68% and 75%, respectively.

The author constructed two models explaining the relationships between the predictability of perceived textures and the degrees of haptic invitation. In the first model, the predictability was supposed to enhance or obscure the effects of sensory factors. In the second model, the predictability was a factor independent on sensory factors. These models described affinity to the textures as well as the models that did not include the predictability. In other words, the including models the author built did not properly describe the influence of predictability. The construction of more sophisticated models remain as future work.

The author summarizes the four findings about a degree of haptic invitation as follows. First, the majority of participants did not feel inclined to touch glossy textures. Second, the participants wanted to touch striped textures more than grid textures because the participants expected intense roughness of striped textures rather than moderate roughness of grid ones. However, the ridge and groove width hardly contribute to the affinity. Third, there was little correlations between the surface colors and degree of haptic invitation. Finally, the linear models did not explain the relationships between the evaluated predictability and the degree of haptic invitation.

The methodology of this study is potentially useful for determining the best combinations among visual factors in terms of material's degree of haptic invitation. In product design, available visual factors tend to be limited. Under such condition, the method enables us to design products or textures that appeal to human touch. The verification of the method in real product design is our next challenge.

Chapter 5

Prominent Perceptual Properties of Materials Determine Invited Behavioral Responses

In Chapter 4, the relationships between degrees of haptic invitation and textural properties were developed. However, the relationships between texture-invited touch motions and textural properties have not been thoroughly investigated. This chapter developed the model representing the probabilistic relationships between perceptual properties of materials and touch motions invited by materials as an example shown in Fig. 5.1. In addition, this chapter conjecture that the difference in touch motions may be a clue to elucidating some of the mechanisms of haptic invitation. This idea is based on that invited touch motions vary for different types of materials [97]. Using the developed probabilistic model (Fig. 5.1), the author experimentally investigates the mechanism of haptic invitation based on the following two propositions.

Proposition 1: Materials with perceptually prominent properties frequently invite human touch motions. Human touch motions may be effectively invited by materials with prominence in textures such as roughness, hardness, and glossiness. Here, textural prominence indicates that one perceptual property is more conspicuous than other properties (see also Sec. 5.2.1). The author conducted sensory evaluations to quantify perceptual properties of materials; then, from the quantified properties, the author calculated their degrees of perceptual prominence. In addition, the author conducted ranking tasks for materials to specify their degrees of haptic invitation. To test Proposition 1, the degrees of textural prominence were compared with the degrees of haptic invitation.

Proposition 2: Invited touch motions are influenced by different types of prominence in properties. An example of this is that, apparently, soft materials may frequently invite pushing, whereas other materials do not. Different types of textural prominence may affect which type of touch motions are likely to be induced, such as stroking or rubbing. To test Proposition 2, the author observed the different touch motions invited by different materials and investigated the relationships between invited touch motions and textural properties.

5.1 Experiment for Constructing Relationships Between Invited Behavioral Responses and Perceptual Responses

Three experiments were performed, in which 14 volunteers (nine males and five females, aged 19–24 years, with no history of deficits in tactile processing, including 10 participants with corrected vision) participated in all three experiments. In Experiment 1, the

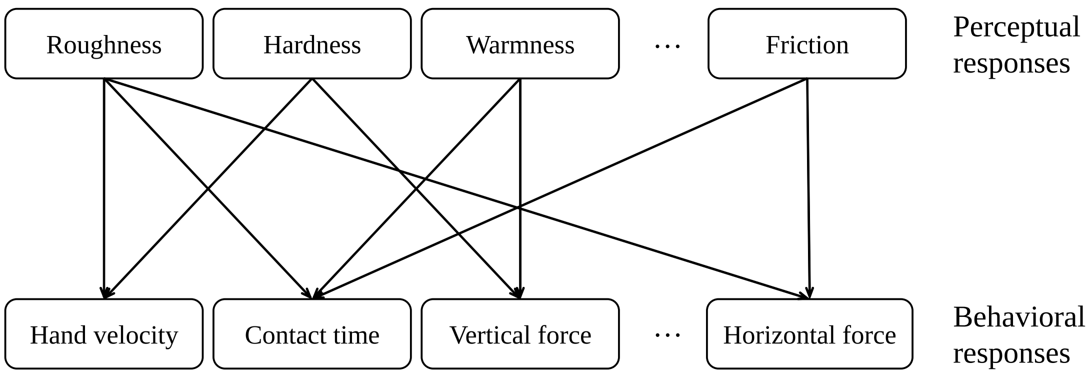

Fig.5.1 Concept the model representing the probabilistic relationships between perceptual properties of materials and touch motions invited by materials

participants visually evaluated the textural properties of materials that were consecutively presented to them by using a semantic differential method. In Experiment 2, the degrees of haptic invitation of materials were calculated based on ranking methods. In Experiment 3, the participants touched materials that strongly invited their touch. Human touch motions were measured using a camera and a six-axis dynamic force sensor. All experimental procedures, including the recruitment of participants, were approved by the Ethics Committee of the Graduate School of Engineering at Nagoya University.

5.1.1 Experimental Materials

Thirty-six materials, which are shown in Fig. 5.2, were used in this study. These were selected from 40 materials through preliminary experiments. In these experiments, five volunteers (five males, aged 21–24 years) ranked the 40 materials, and the degrees of haptic invitation were calculated as shown in Fig. 5.3. The four materials with the highest standard deviations of the degree of haptic invitation as shown in Fig. 5.3 were excluded. The remaining 36 materials, with relatively small individual differences, were selected for the main experiment. A wide variety of materials such as woods, papers, furs, and fabrics were included.

5.1.2 Experiment 1: Sensory Evaluation

The participants evaluated the materials, without touching them by using a seven-point scale in terms of six bipolar adjective pairs: “rough-smooth,” “uneven-flat,” “hard-soft,” “warm-cold,” “sticky-slippery,” and “glossy-glossless,” which the auhto designates as percieved textures of the physical properties of material surfaces, including surface hardness and warmness. The evaluation forms provided these terms in both English and Japanese. Five adjective pairs without “glossy-glossless” were selected based on their commonality with regard to the tactile dimensionality of textures [13]. In addition to these five pairs, glossiness may be an important factor in the visual perception of textures. The author instructed the participants that “uneven” and “rough” meant roughness perceived without and with lateral hand motions, respectively.

As shown in Fig. 5.4a, a large white plate with a 140 mm $\times$ 140 mm square window was placed on a material so that the participants could see only the surfaces and not the sides of the materials. At the beginning of each experiment, the author specified the positions of the material and the participant's head. The distance and angle between the head and material were set to be 600 mm and 45 degrees, respectively. In addition, the participants were instructed to maintain their head positions during experiments to retain their relative positions between head and material. The materials and adjective pairs were presented to each participant in random order.

Ratings from 1 to 7 were assigned on a seven-point adjective scale that was used to perform measurements in the experiments. These ratings were normalized for a single participant such that the mean and standard deviation became 0 and 1, respectively.

The degrees of textural prominence were calculated from the absolute values of six textural properties. Smaller absolute values of the textural property indicate that the ma-

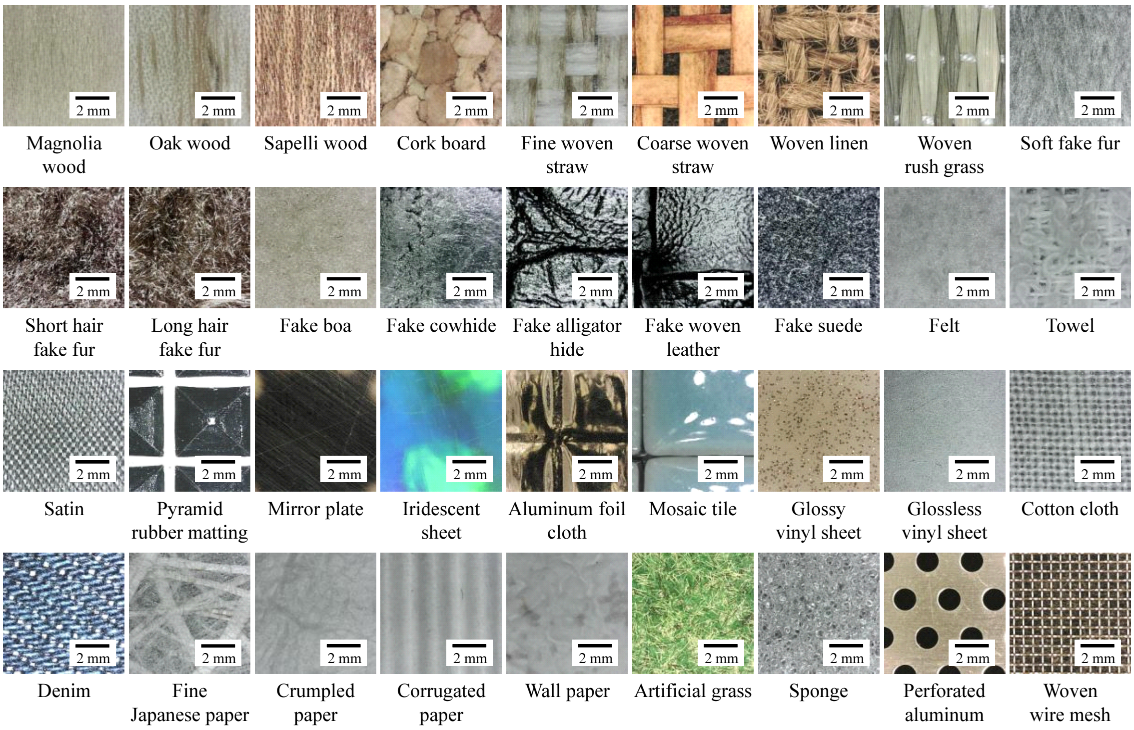

Fig.5.2 Thirty-six materials used in experiments

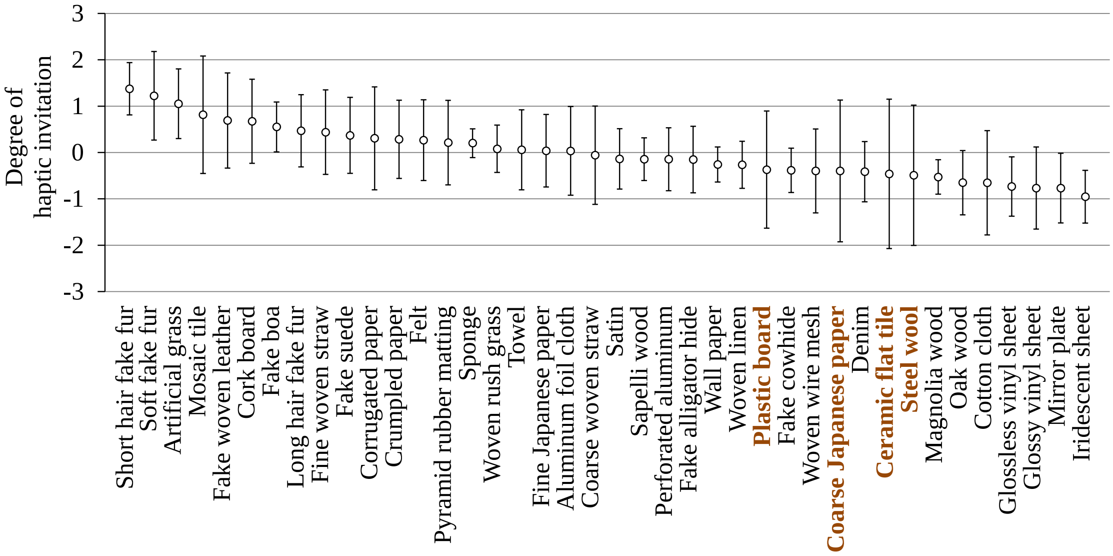

Fig.5.3 Degrees of haptic invitation for forty materials (mean+/-SD). The four materials (written in bold fonts) with the highest standard deviations of the degree of haptic invitation were excluded from the main experiment. As a result those with the SD higher than 1.26 were excluded.

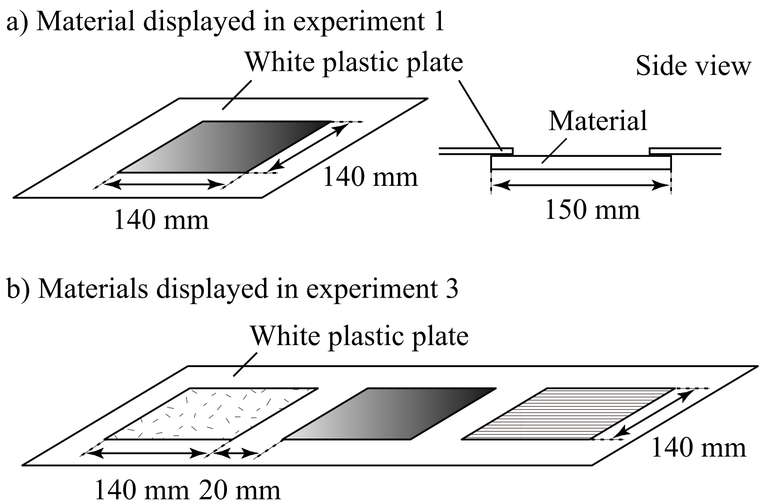

Fig.5.4 Presentation method of materials

terials evaluated are neutral in terms of that property. In contrast, larger absolute values indicate that materials take extreme values on that bipolar axis. The degree of prominence for a material specified by j was determined as follows:

$$\begin{aligned} Pr_j = &\max(|x_{jk}|, k = 1, 2, \cdots, 6) \\ &-\mathrm{ave}(|x_{jk}|, s.t. |x_{jk}| \neq \max(|x_{jk}|)). \end{aligned} \tag{5.1}$$

where x_{jk} is the evaluation value of an adjective pair specified by k for material j. The degree of prominence was assigned as the difference between the maximum value among the six evaluation values and the averaged value of the remaining five evaluation values. Thus, the degree of prominence represents the extent to which the most impressive property among six properties is prominent, compared with the other five properties.

5.1.3 Experiment 2: Ranking 36 Materials

The degrees of haptic invitation of the materials was calculated on the basis of the ranking methods that were introduced in a previous study [98]. The participants ranked 36 materials in order of the extent to which they felt inclined to touch them. The materials were simultaneously presented to each participant. In the earlier study [98], the majority of participants answered that it was easier to choose materials with higher and lower degrees of haptic invitation and that it was not easy to rank the other neutral materials. These opinions suggested that the ranks of haptic invitation should not be treated as equal interval scales. The author then converted the ranks to interval scales as expected values of a standard normal distribution [87]. These values represent the degrees of haptic invitation of the materials. The degree of the ith-ranked material was assigned as the expected value of the ith largest observation in a sample of size n from a standard normal population. The degree of the ith-ranked material was determined as follows:

$$E(x_{i|n}) = \frac{n!}{(n-i)!(i-1)!} \int_{-\infty}^{\infty} x \cdot a(x) \cdot b(x) \cdot \phi(x) dx \tag{5.2}$$

$$a(x) = \left[\tfrac{1}{2} - \Phi(x)\right]^{i-1} \tag{5.3}$$

$$b(x) = \left[\tfrac{1}{2} + \Phi(x)\right]^{n-i} \tag{5.4}$$

$$\phi(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\tfrac{1}{2}x^2\right) \tag{5.5}$$

$$\Phi(x) = \int_0^x \phi(z) dz. \tag{5.6}$$

The degrees of haptic invitation for a given texture were averaged across the participants.

5.1.4 Experiment 3: Observation of Touch Motions

Among the three materials offered to them, participants touched the one material that they felt most strongly invited their touch. The materials were placed under a white plastic plate, as shown in Fig. 5.4b. If only one material was shown in each experiment, the participant would only be able to touch that one. Therefore, to avoid this unnatural situation, three materials were shown to the participants.

The participants were instructed to close their eyes before the experimenter arranged the three stimuli. They were instructed to "keep your eyes closed until you hear a beep sound, after which freely touch the one you feel most inclined to touch," in which a sound cue became a reference for the participants' response times. Their hand movements were not restricted at all by instructions; however, most participants touched materials with their index finger. This was clearly done because they knew that a camera captured the motion of their index finger with an attached marker.

Combinations of three materials were determined based on the average ranks of haptic invitation. One of three materials was randomly selected from among the 12 materials that exhibited the highest degrees of haptic invitation among 36 materials. At random, a second material was selected from the lowest 12 materials, and a third was selected from the remaining 12 materials. Hence, 12 combinations were presented to each participant in random order. Then, using the 24 materials that had not been touched in the first round, eight more combinations were determined through a process similar to that described above, and were then presented to the participant. In total, each participant thus received a unique set of 20 combinations (12 and eight in the first and second rounds, respectively). The material sets for the first participant were only based on his or her ranking of materials and those of the preliminary experiments involving five volunteers (five males, aged 21–24 years). The degrees of haptic invitation were updated every time new degrees were obtained in Experiment 2. The ranking in the preliminary experiment was not exactly same as the final rankings in the main experiment. For example, the rank of fine woven straw changed most: from ninth to 23rd.

Human touch motions to materials were measured as shown in Fig. 5.5. The tip position of each participant's index finger was measured using a camera (Firefly MV, Point Grey Research Inc., Richmond, Canada, 640 $\times$ 480 pix, 60 fps). This position was detected from a red marker that was fixed on the metacarpophalangeal joint of the index finger. The contact forces were measured using a six-axis dynamic force sensor (MINI 2/10, BL AUTOTEC. LTD., Kobe, Japan) at a sampling frequency of 60 Hz. The sensor was fixed under a metal plate on which the materials were placed.

5.2 Proposition 1: Prominence Invites Touch

To test Proposition 1, which posits that materials with prominent textures frequently invite human touch motions, two analyses were conducted. In the first analysis, degrees of haptic invitation were compared with degrees of visual prominence in textures. These degrees of prominence were based on the results of Experiment 1. In the second analysis, materials were classified into two groups (touched and untouched materials) based on the results of Experiment 3. A comparison between the two groups was then performed, in terms of degrees of prominence.

5.2.1 First Analysis: Correlation Between Perceptual Prominence and Haptic Invitation

The degrees of both textural prominence and haptic invitation were averaged across the participants and then compared. The degrees of haptic invitation for thirty-six materials and the relationships between the degrees of textural prominence and haptic invitation are shown in Figs. 5.6 and 5.7, respectively. The correlation coefficient was 0.53 ($t(34) = 3.6$, $p = 9.6 \times 10^{-4}$). Materials with higher degrees of prominence more effectively invited human touch. This finding supports Proposition 1. However, because our finding is simply correlation and its coefficient is not substantially high, a relationship between prominence and haptic invitation may be mediated by other factors.

Some of the six ratings may have been correlated with each other. In such a case, our definition of prominence value ineffectively specifies the textural prominence. To organize a set of uncorrelated ratings, the author applied a factor analysis to the six ratings. As a result, as listed in Table 5.1, the textural properties were effectively represented

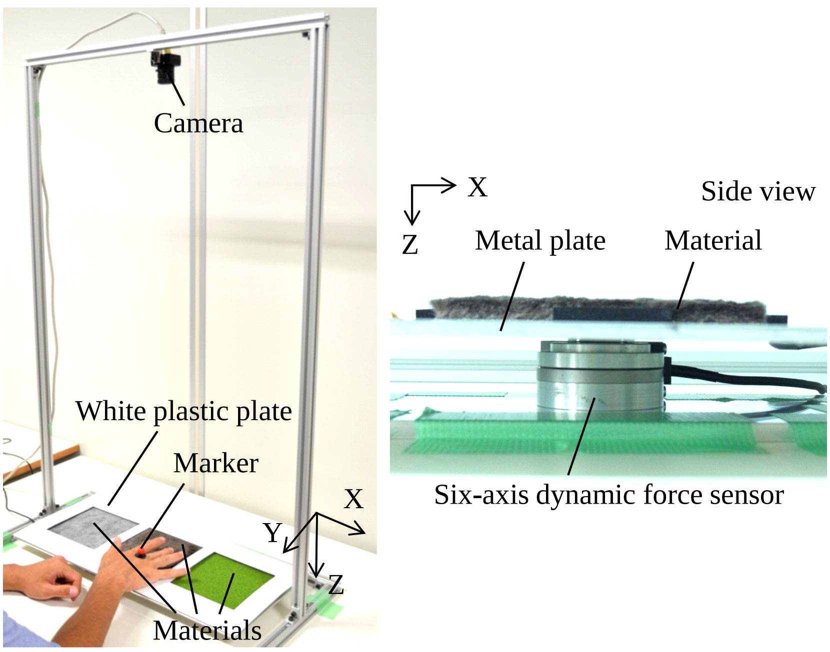

Fig.5.5 Measurement of touch motions to textures

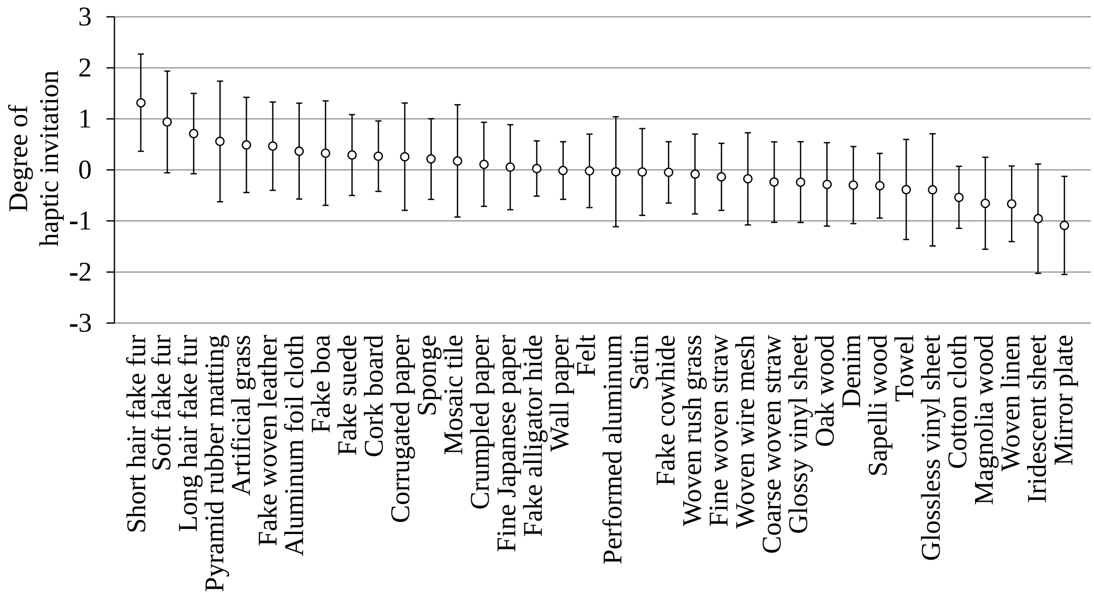

Fig.5.6 Degrees of haptic invitation for thirty-six materials. Mean and standard deviations among the participants.

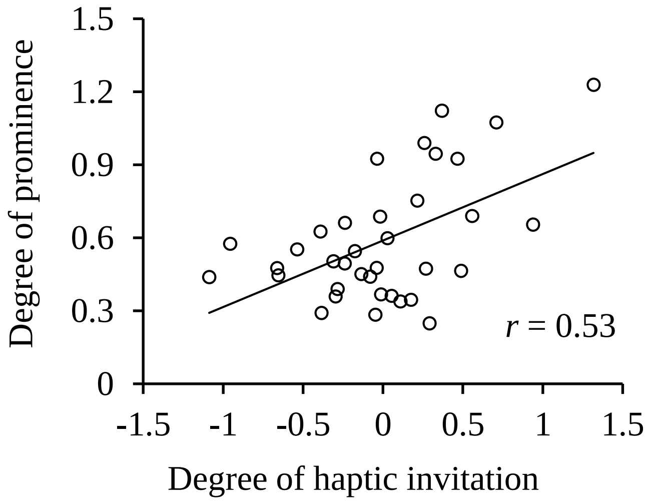

Fig.5.7 Correlation between degree of perceptual prominence for six properties and degree of haptic invitation. The solid line is a regression line.

by three factors. The degrees of textural prominence that were calculated from these uncorrelated variable sets were not well correlated with degrees of haptic invitation, with a correlation coefficient of 0.36 ($t(34) = 2.3$, $p = 3.5 \times 10^{-2}$) as shown in Fig. 5.8. The visual prominence values calculated by factors specified for a material set yielded lower correlation with the degrees of haptic invitation than those the general prominence values calculated by the six textural properties. The resultant structure of factor analysis depends on the stimuli set. With different material sets, a structure may change. In the latter analysis, to maintain generality, the author used six textural properties rather than the three factors acquired here.

5.2.2 Second Analysis: Comparison Between Degrees of Prominence for Touched Versus Untouched Materials

The stimuli were divided into groups of touched and untouched materials. Because each of the 14 participants took part in the 20 trials in Experiment 3, the touched and untouched groups contained 280 and 224 samples, respectively. Fig. 5.9 shows the number

Table 5.1 Results of factor analysis: Factor loadings of six adjective pairs

	Factor 1	Factor 2	Factor 3
Micro roughness	0.96	0.00	−0.26
Macro roughness	0.73	0.06	0.06
Hardness	−0.11	−0.83	0.15
Warmness	0.10	0.94	−0.33
Friction	0.78	0.35	−0.30
Glossiness	−0.21	−0.48	0.85
Contributing rate	0.56	0.27	0.09
Cumulative contributing rate	0.56	0.83	0.92

of touches for all materials in comparison with the degree of haptic invitation specified in Experiment 2. These numbers are well correlated with the degrees of haptic invitation. The two groups of touched and untouched materials were compared in terms of their average degrees of prominence. As shown in Fig. 5.10, the degrees of prominence of touched materials were significantly greater than those of untouched materials ($t(502) = 6.7$, $p = 6.3 \times 10^{-11}$). In other words, the materials that invited the participants' touch had more prominent textures; this finding is also consistent with Proposition 1.

5.3 Proposition 2: Touch Motion Depends on Prominence

To test Proposition 2, which posits that invited touch motions are influenced by different types of textural prominence, the author constructed a Bayesian network model that offers conditional probabilities between the invited touch motions and the properties of textures. The model simply connects the simultaneous occurrence of events, which quantitatively analyze statistical relationships while negating the need to discuss any mathematical relationships between them. Using touch motions as evidence, the model estimated the

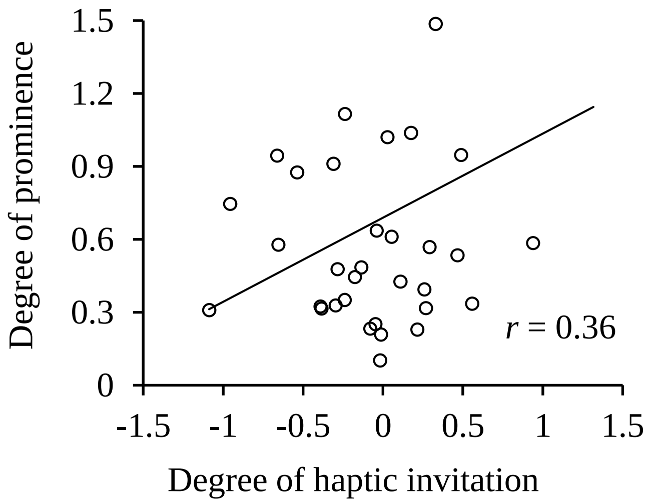

Fig.5.8 Correlation between degree of perceptual prominence for three factors and degree of haptic invitation. The solid line is a regression line.

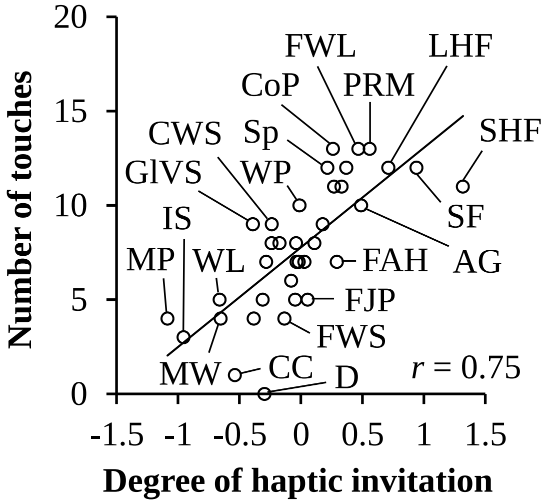

Fig.5.9 Relationships between the number of touches and degree of haptic invitation. LHF: Long hair fake fur; FWL: Fake woven leather; PRM: Pyramid rubber matting; CoP: Corrugated paper; SHF: Short hair fake fur; Sp: Sponge; CWS: Coarse woven straw; WP: Wall paper; GlVS: Glossless vinyl sheet fur; SF: Soft fake fur; IS: Iridescent paper; AG: Artificial grass; FAH: Fake alligator hide; WL: Woven linen; MP: Mirror plate; FJP: Fine Japanese paper; FWS: Fine woven straw; D: Denim; CC: Cotton cloth; MW: Magnolia wood.

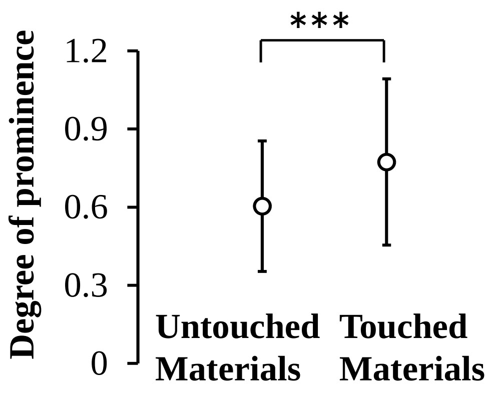

Fig.5.10 Degrees of prominence of touched and untouched materials. The error bar and asterisk symbols *** indicate the standard deviation of prominence and significance level of $p < 0.001$, respectively.

properties of textures that frequently invite such motions. The results of these estimations would address Proposition 2.

5.3.1 Construction of a Probabilistic Model

From the results of experiments 1 and 3, the author extracted nodes that constructed a probabilistic network. There were three types of nodes: properties of textures, touch motions, and touch mode. A touch mode node is a meta node that represents types of touch behaviors. This node was determined from the ensemble of touch motions. The primitiveness of touch motions makes them helpful to interpret the physical interactions between touch and materials. In contrast, touch modes are more intuitive in the exchange of a lack of detailed information about motion dynamics. These nodes were all discrete variables, and are described in detail below.

Perceptual Properties of Materials

Six nodes were created based on the adjective ratings "rough-smooth," "uneven-flat," "hard-soft," "warm-cold," "sticky-slippery," and "glossy-glossless," which were taken from Experiment 1. These ratings were quantified into three levels with two boundaries (-0.43, 0.43) that divided the occurrence probability equally into three. For example, for one participant, the standardized "rough-smooth" rating of soft fake fur was -1.1 (+: rough; −: smooth), which was lower than -0.43. Therefore, the *micro roughness* node was labeled "smooth." The six adjective ratings were quantified in the following manner.

Micro Roughness: Smooth, moderate, or rough.

Macro Roughness: Flat, moderate, or uneven.

Hardness: Soft, moderate, or hard.

Warmness: Cold, moderate, or warm.

Friction: Slippery, moderate, or sticky.

Glossiness: Glossless, moderate, or glossy.

Touch Motions

Human touch motions were measured using a camera and a force sensor. The measured data were normalized for each participant, and the author produced 11 nodes from the normalized data. As in the case of the textural properties, the following nodes were all discretized into their qualitative states with two boundaries (-0.43, 0.43).

Time before touch: Short, moderate, or long. The *time before touch* node was determined from the period between the time at which a sound cue was presented to a participant, and the time at which the force signal began to change. For example, for one participant, the normalized value of *time before touch* for cork board was 2.2 ($+$: long; $-$: short), which was higher than 0.43. Therefore, the *time before touch* node of cork board was assigned the label "long."

Contact period: Short, moderate, or long. The *contact period* node was determined as the period during which a material was being touched.

Maximum normal force: Weak, moderate, or strong. The *maximum normal force* node was determined from the maximum Z-axial force exerted while the participant was in contact with a material.

Average normal force: Weak, moderate, or strong. The average Z-axial force during contact determined the *average normal force* node.

Maximum tangential force: Weak, moderate, or strong. The *maximum tangential force* node was the maximum resultant force of the X and Y-axial forces applied to a material.

Average tangential force: Weak, moderate, or strong. The average X-Y resultant force during contact determined the *average tangential force* node.

Maximum force rate: Low, moderate, or high. The author defined the ratio of the Z-axial force to the X-Y resultant force as the force rate. This node was the maximum value of the force rates while the participant was in contact with the material.

Average force rate: Low, moderate, or high. This node is the average force rate.

Maximum hand velocity: Slow, moderate, or fast. The author calculated the participants' hand velocities from the time series data of their hand positions that were captured on camera. The maximum value of hand velocities during participants' contact with a material determined the *maximum hand velocity* node.

Average hand velocity: Slow, moderate, or fast. This node is the average hand velocity while a participant is in contact with a material.

Travel distance: Short, moderate, or long. The *travel distance* node was determined from the total distance traveled by a hand while it was in contact with a material.

Touch Mode

The *touch mode* node was defined as being representative of the typical modes of invited touch motions. Using a cluster analysis that employed Ward's method [99], the author classified the 280 trials in Experiment 3 into a number of groups on the basis of the 11 touch motions, as described above. The Euclidean distances between trials were calculated from the values of the 11 touch motions. Ward's method adopts these Euclidean distances as a dissimilarity matrix and merges the two trials with the minimum dissim-

Table 5.2 Average touch motion values of each touch mode. The asterisk symbols $***$ indicate the significance level of $p < 0.001$

	Touch mode			
Touch motion	Push	Rub	Stroke	Soft touch
Time before touch	−0.02	0.13	−0.08	0.06
Contact period	0.10	0.11	0.70***	−0.85***
Max. normal force	1.74***	−0.06	−0.11	−0.63***
Ave. normal force	1.83***	−0.07	−0.16	−0.60***
Max. tangential force	0.74***	1.35***	−0.03	−0.70***
Ave. tangential force	0.27	1.65***	−0.02	−0.58***
Max. force rate	1.46***	−0.45***	0.00	−0.51***
Ave. force rate	1.80***	−0.62***	−0.20***	−0.39***
Max. hand velocity	−0.53***	−0.02	0.35***	−0.14
Ave. hand velocity	−0.94***	−0.31	0.25***	0.24
Travel distance	−0.53***	−0.18	0.77***	−0.56***

ilarity into a new cluster. Repetitive fusions decreased the number of clusters into four. Table 5.2 lists the average values of touch motions for each touch mode. The figures with asterisk symbols are significantly different from zero, and represent the feature of the mode.

Touch mode: Push, rub, stroke, or soft touch. Based on the features described in Table 5.2, the four types of touch mode were assigned as push, rub, stroke, and soft touch. For example, the mode with strong normal forces and slow hand velocities was called "push." The author next describe some examples of touch motions that characterize these four modes: push (*max. and ave. normal force*: strong, *max. and ave. hand velocity*: slow), rub (*max. and ave. tangential force*: strong, *max. and ave. force rate*: low), stroke (*max. and ave. hand velocity*: fast, *travel distance*: long), and soft touch (*max. and ave. normal force*: weak, *travel distance*: short).

Model Structure

The Bayesian network structure was determined from the discretized data of six properties, touch motions, and touch mode, by using a greedy search algorithm with Akaike Information Criterion [100] as the evaluation score. The arcs of the network were restricted such that they did not mutually connect textural properties. The same rule was applied to touch motions. In addition, the arcs between textural properties and touch mode were not permitted. The constructed model is presented in Fig. 5.11.

5.3.2 Probabilistic Estimation

To test Proposition 2, the author investigated the probabilistic relationships between the textural properties and the touch motions or mode. The probabilities of the textural properties were estimated using the touch motions and mode as evidence. As shown in Fig. 5.11, two connected nodes have a statistical relationship, and potentially a causal relationship. The author do not mention all of these connections, but the author focuses on the connections with the largest probabilistic deviations for each textural property. Hence, the author describe seven connections as follows.

Micro Roughness **(Rough/smooth) and** *Travel Distance*

To investigate the relationships between the *travel distance* and *micro roughness* nodes, the author estimated the probabilities of the *micro roughness* node from the *travel distance* node that was given as evidence. The estimation results are listed in Table 5.3. Cells with probabilities of 0.45 or higher are highlighted in gray. This value is the border of the statistically significant interval ($\chi^2(2) = 5.99$, $p = 0.05$, $N = 93$) in the occurrence number of events between the probability set (0.453, 0.273, and 0.273) and the expected set (0.333, 0.333, and 0.333). The probabilities of *micro roughness* being rough were the highest, at 0.62 and 0.55, when the *travel distance* nodes were long and moderate, respectively. When the participants experience apparently rough materials, it is reasonable for them to stroke these materials broadly to effectively produce vibrotactile cues. Such skin vibration caused by exploratory movements plays a significant role in the perception of micro roughness [65, 50].

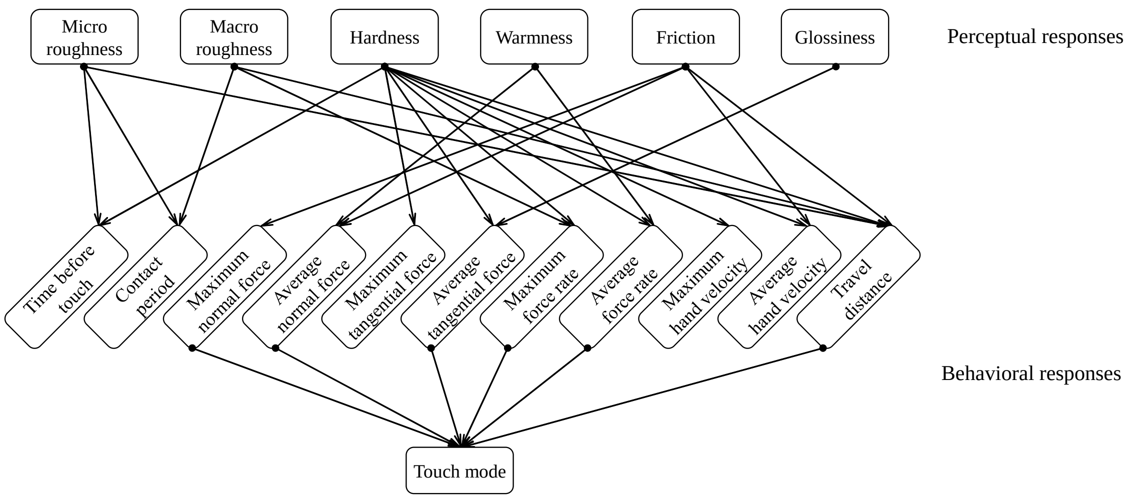

Fig.5.11 Bayesian network model connecting textural properties, invited touch motions, and touch mode

Macro Roughness **(Uneven/flat) and** *Maximum Force Rate*

The author estimated the probabilities of *macro roughness* by using the *maximum force rate* as evidence. As shown in Table 5.4, when the *maximum force rate* node was low, the probability of *macro roughness* being flat was 0.53. This trend implied that, for flat materials, the normal forces were relatively weaker than the tangential ones. Flat materials were also accompanied by large travel distances. Because overly large normal forces hinder such hand movements, this low force rate is strategic for the perception of flat surfaces. In addition, given that the *maximum force rate* node was high, the network estimated that the probability of *macro roughness* being uneven was 0.58. Participants tended to touch uneven materials with relatively stronger normal forces than tangential ones. In the perception of macro roughness, lateral hand movements are not necessary to a great extent, because surface unevenness is perceived as the unevenness of pressure sensations rather than as vibrotactile information [65, 101]. Therefore, touch motions with high normal to tangential force ratios are potentially appropriate for perceiving the surface unevenness of materials.

Hardness **(Hard/soft) and** *Average Force Rate*

As shown in Table 5.5, given the state of the *average force rate* node as evidence, the network estimated the probabilities of the *hardness* node. When the *average force rate* node

Table 5.3 Probabilities of *micro roughness* when *travel distance* is given as evidence

Estimated result:	Evidence: Travel distance		
Micro roughness	Short	Middle	Long
Smooth	0.35	0.26	0.24
Middle	0.25	0.19	0.14
Rough	0.40	0.55	0.62

was high, the probability of *hardness* being soft was the highest, at 0.61. In other words, the normal forces for apparently soft materials were relatively stronger than the tangential forces. The perception of softness or elasticity seems to be related to information received from the contact area of the finger pads, such as spatial pressure distributions, and the relationships between the force and the contact area or the force and the displacement that takes place during pushing by fingers [67, 70, 102]. Therefore, in the experience of material softness, touch motions with a high *average force rate* were appropriate.

Warmness **(Warm/cold) and** *Average Normal Force*

Table 5.6 lists the probabilities of the *warmness* node when the *average normal force* is given as evidence. When the *average normal force* node was strong, the probability of *warmness* being warm was the highest, at 0.48. In other words, participants tended to use strong normal forces for touching apparently warm materials. Touch motions such as pushing increase the contact area between fingers and material, which allows human to effectively perceive surface warmness because a large contact area enhances heat transfer. This strategy is especially effective for warm-looking materials, and not as effective for cold-looking ones. This is because when the potential difference between the temperature

Table 5.4 Probabilities of *macro roughness* when *maximum force rate* (normal / tangential forces) is given as evidence

Estimated result:	Evidence: Maximum force rate (normal / tangential forces)		
Macro roughness	Low	Middle	High
Flat	0.53	0.32	0.25
Middle	0.15	0.24	0.17
Uneven	0.32	0.44	0.58

of the skin and that of the material is large enough for humans to detect, a measure that fosters heat transfer is not required. On the other hand, because the heat transfer between the skin and a warm material is limited (here, being warm means that its temperature is close to that of human skin), the reduction in thermal resistance owing to higher pressure and the resulting large contact area is effective for detecting subtle differences in temperature.

Table 5.5 Probabilities of *hardness* when *average force rate* (normal / tangential forces) is given as evidence

Estimated result:	Evidence: Average force rate (normal / tangential forces)		
Hardness	Low	Middle	High
Soft	0.33	0.44	0.61
Moderate	0.25	0.21	0.19
Hard	0.42	0.35	0.19

Table 5.6 Probabilities of *warmness* when *average normal force* is given as evidence

Estimated result:	Evidence: Average normal force		
Warmness	Weak	Middle	Strong
Cold	0.39	0.25	0.17
Moderate	0.30	0.33	0.35
Warm	0.31	0.42	0.48

Friction **(Sticky/slippery) and** *Maximum Normal Force*

The author estimated the probabilities of the *friction* node from the *maximum normal force* node that was given as evidence. As shown in Table 5.7, when the *maximum normal force* node was strong, the probability of *friction* being sticky was 0.56. Furthermore, given that the *maximum normal force* node was weak, the network estimated that the probability of *friction* being slippery was 0.55. When participants touched slippery materials, they tended to use weak normal forces. The use of strong normal forces for sticky materials allowed participants to experience their large frictional properties, and weak normal forces were appropriate for them to effectively experience the surface slipperiness of materials. These findings are supported by previous studies [75, 103], which reported the relationships between the shear deformations caused by tangential forces applied to finger pads and the perception of friction.

Glossiness **(Glossy/glossless) and** *Average Tangential Force*

Table 5.8 lists the probabilities of the *glossiness* node when the *average tangential force* is given as evidence. When the *average tangential force* node was weak, the probability of *glossiness* being glossless was the highest, at 0.60. On the other hand, when the *average tangential force* node was strong, the probability of the textures being glossy was 0.55. Because glossy materials tend to look frictional, explanations similar to those given

Table 5.7 Probabilities of *friction* when *maximum normal force* is given as evidence

Estimated result:	Evidence: Maximum normal force		
Friction	Weak	Middle	Strong
Slippery	0.55	0.31	0.27
Moderate	0.12	0.32	0.17
Sticky	0.33	0.37	0.56

in Sec. 5.3.1 are also valid here. For glossy and apparently frictional materials, the participants touched them with large tangential forces. Such forces cause substantial stretching of the skin, which enables humans to experience a large degree of friction.

Touch Mode and Six Perceptual Properties of Materials

The probabilistic relationships between the six properties and *touch mode* are listed in Table 5.9. When the *touch mode* node is "push," the probability of *hardness* being soft is 0.55, and that of it being hard is 0.18. Apparently soft materials are likely to invite the push mode, whereas hard materials are not. On the other hand, the rub mode is likely to be invited by hard materials. Stroke and soft touch modes are not strongly related to the apparent softness of materials (*hardness*). As shown in Table 5.9, each textural property, except for *friction*, is probabilistically linked with *touch mode*.

Multiple Evidences for Estimating Perceptual Properties

The author estimated the probabilities of textural properties given multiple touch motions as evidence, in addition to the estimations from single evidence as described above. It is of interest to us to determine whether the types of textures can be fully identified from the observed touch motions. Unfortunately, these probabilities were not significantly higher than those inferred by single evidence, which indicates that the textures are unlikely to

Table 5.8 Probabilities of *glossiness* when *average tangential force* is given as evidence

Estimated result:	Evidence: Average tangential force		
Glossiness	Weak	Middle	Strong
Glossless	0.60	0.44	0.39
Moderate	0.12	0.13	0.06
Glossy	0.28	0.43	0.55

be fully identified by the motion parameters used in the present study. However, the established network is still valuable for discussing the trends of textures and touch motions with moderate probabilistic deviations.

Table 5.9 Probabilities of six perceptual properties of materials when *touch mode* is given as evidence

		Evidence: Touch mode			
		Push	Rub	Stroke	Soft touch
Estimated result: Micro roughness	Smooth	0.28	0.33	0.20	0.38
	Moderate	0.30	0.16	0.17	0.20
	Rough	0.42	0.51	0.63	0.42
Estimated result: Macro roughness	Flat	0.23	0.42	0.44	0.44
	Moderate	0.22	0.20	0.14	0.17
	Uneven	0.55	0.38	0.42	0.39
Estimated result: Hardness	Soft	0.55	0.25	0.39	0.43
	Moderate	0.27	0.18	0.30	0.20
	Hard	0.18	0.57	0.31	0.37
Estimated result: Warmness	Cold	0.15	0.43	0.33	0.45
	Moderate	0.40	0.24	0.32	0.27
	Warm	0.45	0.33	0.35	0.28
Estimated result: Friction	Slippery	0.28	0.42	0.37	0.41
	Moderate	0.28	0.20	0.23	0.19
	Sticky	0.44	0.38	0.40	0.40
Estimated result: Glossiness	Glossless	0.43	0.33	0.54	0.44
	Moderate	0.32	0.12	0.14	0.33
	Glossy	0.25	0.55	0.32	0.23

5.3.3 Probabilistic Estimations Support Proposition 2

Table 5.10 summarizes Tables 5.3–5.9 and lists the likely connections between the touch mode and textural properties. As listed in the table, the touch mode is probabilistically connected to the prominent properties of texture. In addition, such connections are not accidental but are intuitively reasonable in terms of the previously described human perceptual strategies. These probabilistic trends fairly indicate that certain prominent textures tend to invite certain hand movements.

The push mode is frequently invited by apparently uneven, soft, or warm materials. This mode is represented by strong normal forces and small travel distances. As described earlier, such a motion is appropriate for testing these textural properties. A pushing motion allows us to experience a material's spatial unevenness within the contact area, its softness via the pressure of our finger pads, and its warmness via the heat transfer that is enhanced by the increased contact area. Further, lateral hand movements are dispensable to the experience of unevenness, softness, and warmness.

Table 5.10 Touch modes and textural properties that are likely to invite touch motions. The representative materials in the table satisfy all of the listed textural properties. For example, the average ratings of fake woven leather were uneven, soft, and warm.

Touch mode	Property of texture	Representative materials
Push	Macro roughness: uneven (55%), Hardness: soft (55%) Warmness: warm (45%)	Fake woven leather, Sponge
Rub	Micro roughness: rough (51%), Hardness: hard (57%), Glossiness: glossy (55%)	Perforated aluminum, Woven wire mesh
Stroke	Micro roughness: rough (63%), Glossiness: glossless (54%)	Artificial grass, Coarse woven straw
Soft touch	Warmness: cold (45%)	Satin

The rub and stroke modes are often used for exploring rough materials. This is intuitively reasonable because these modes, which include lateral hand movements, produce the information needed to decode surface roughness. Meanwhile, the rub mode is often invited by glossy materials, whereas the stroke mode is invited by glossless ones. One of the major differences between these two touch modes lies in the magnitude of the tangential forces. The rub mode involves larger tangential forces than the stroke mode. Tangential forces are linked with the perception of friction. The rub mode is better suited to glossy materials than the stroke mode because the large tangential forces of the rub mode are more relevant to the experience of potentially high coefficients of friction.

The soft touch mode has a probabilistic link with apparently cold materials. This mode has weak normal forces and short contact periods. Such a motion is sufficient for heat transfer between a person's fingers and a cold material, a circumstance in which the temperature difference is large, and this heat can thus be detected by the fingers' temperature-sensitive receptors. The soft touch mode is an economic motion for feeling the coldness of materials.

The above mentioned results demonstrate that types of prominent textures influence invited touch motions, a finding that supports Proposition 2.

5.4 Summary of Chapter 5

In this chapter, a series of experiments are conducted for investigating the potential mechanism of haptic invitation, which is a phenomenon in which the textures of materials invite human touch motions. The many analyses of the results positively indicated two propositions underlying haptic invitation. First, materials with visually prominent textures frequently invite human touch motions. Second, invited touch motions are influenced by the types of prominent textures.

With regard to the first proposition, a positive correlation coefficient of 0.53 was observed between the degrees of haptic invitation and textural prominence. This coefficient decreased to 0.36 in the case that the prominence values were calculated based on the factorial values that integrated the correlated textural properties. Furthermore, the degrees of textural prominence of materials that invited touch motions in Experiment 3 were higher than those of materials that were not touched. These results support the first proposition; namely, that materials with a prominent texture effectively invite human touch. However, the coefficient values were not substantially large and the correlation always indirectly linked two events. The prominence may be one contribution, and other factors may also pertain to haptic invitation.

With regard to our second proposition, the author constructed a Bayesian network model that represented the probabilistic relationships between the invited touch motions and the properties of textures. The model corroborated the idea that invited touch motions and touch modes vary, depending on the different types of prominence in textures.

As described above, perceptual prominence in textures tends to invite human touch motions, and types of prominent textures are likely to invite appropriate touch motions. Haptic invitation increases the probability that people will make contact with textures as haptic inputs, which can be sensed through economic motions for textures, unlike passive visual or auditory stimuli. The author interpret the haptic invitation of material as a phenomenon in which the textural prominence of a material encourages us to feel it. One rational role of this phenomenon is to maintain the system whereby individuals recognize tactile textures, because the increase in the probability of touching prominent textures may be instrumental in activating human perceptual systems.

Chapter 6

Conclusions and Future Perspectives

This thesis proposed computational methods for determining relationships among perceptual, emotional, and behavioral responses. First, the author developed a construction method for a multilayered model of perceptual, emotional, and preferential responses to materials. This method can help to understand fully the mechanisms of tactile perception or emotion. In addition, it can aid in effectively designing consumer products through estimations of perceived impressions to the products. Second, the author established a computational method to determine the relationships among factors of materials and degrees of haptic invitation. Finally, the author developed a method for constructing probabilistic relationships among touch responses and perceptual properties of materials. These methods support us in designing materials or products that frequently invite human responses of touch. Each method was validated through a case study. The results and future perspectives of individual chapters are summarized below.

Chapter 2: Psychophysical Dimensions of Perceptual Responses In Chapter 2, we investigated many studies related to psychophysical dimensions of perceptual responses, and then determined the common structure of psychophysical spaces. The roughness, warmness, and hardness dimensions were frequently extracted as psychophysical dimension. In addition, some studies reported that roughness perception could be divided into macro and fine roughness dimensions. These two types of roughness can be regarded as separate dimensions because of the different mechanisms of perception that are involved. In addition, many studies examined the dimension related to moist/dry and sticky/slippery adjectives. These dimensions can be considered a single dimension that is mediated by the friction of materials. Thus, we concluded that the psychophysical dimensions of perceptual responses are composed of five dimensions: macro and fine roughness, warmness, hardness, and friction. No single experiment has yet to extract all five psychophysical dimensions. The differences in the extracted dimensions can be derived from the differences of experimental and analytical methods, materials, and adjectives. Factor analyses and multidimensional scaling methods reduce the likelihood of detecting weak dimensions. Thus, a balanced material set is necessary for extracting balanced dimensions. In a semantic differential method and in a post hoc validation of dimensions, adjectives that describe the five dimensions should be used. The experimenter should use at least those materials and adjectives that represent the five psychophysical dimensions. Identifying the five dimensions in a single experiment is a task for future studies.

Chapter 3: Multilayered Model of Perceptual, Affective, and Hedonic Responses
In Chapter 3, the author developed a computation method for a multi-layered model of internal responses that occur after surfaces are touched. The developed method consists of two processes. First, in order to determine a structure for a model of adjectives representing human internal responses, we evaluate causalities between adjectives. Next, using sensory evaluation and multivariate statistical analysis, the author could statistically estimate undefined parameters, including the strength of relationship between adjectives in a constructed structure. To validate the developed method, we attempted to construct a model that represents the relationships between touch-related internal responses based on experiments. The constructed model consists of three layers that include adjectives that represent psychophysical, affective, and hedonic responses, respectively. This semantic trend indicates that our developed method can help us construct a semantic multi-layered model of internal responses to the materials set used in the study. In the developed method, a threshold value determines a model structure. Thus, using several types of thresholds, the author constructed models with different numbers of nodes and arcs, and then calcu-

lated fit indices for sensory evaluation data of each model. For the material set used in this study, one constructed model demonstrated a satisfactory performance (CFI of 0.93) for representing internal responses.

The proposed method supports the estimation and design of various internal responses related to product design. Accordingly, relationships between adjectives in the psychophysical layer and physical properties of materials must be determined. For example, Akay et al. [104] identified the relationships between the six adjectives ("rough/smooth," "bumpy/flat," "hard/soft," "warm/cold," "sticky/slippery," and "wet/dry")and the physical properties of textured surfaces (e.g., friction coefficients and average roughness). Other studies, such as [27, 31, 105], have showed the relationships between perceptual and physical properties of materials. By using a multilayered model that connects the psychophysical to the affective and hedonic layers, physical properties affecting internal responses in the uppermost layers can be predicted.

Chapter 4: Perceptual Responses and Physical Properties that Affect the Degree of Haptic Invitation Chapter 4 developed a computational method of haptic invitation, which occurs when surfaces provoke or invite a touch response. The author assumed that visual (i.e., the physical properties of materials) and sensory factors(i.e. internal responses to materials) may be related to degrees of haptic invitation. The author thus established relationships among visual and sensory factors of materials and the degree of haptic invitation. The four visual factors are: surface color, gloss, shape type, and ridge-groove width. The four sensory factors are: dry, uneven, cold, and simple. The degrees of haptic invitation are measured by means of a ranking system and the normalized-rank approach. Regarding visual factors, the glossiness and surface shape types of materials strongly affected the degree of haptic invitation. No correlation between the surface colors and degree of haptic invitation was revealed through additional experiments. Regarding sensory factors, dry and simple factors strongly affected the degree of haptic invitation. Multiple regression analyses revealed that the visual and sensory factors effectively described the degrees of haptic invitation with accuracies of 68 and 75%, respectively.

The results show that the proposed methodology is potentially useful for determining the best combinations among visual factors in terms of a material's degree of haptic invitation. However, the remaining unexplained 20–30% of variance may be due to the visual and sensory aspects of materials that were omitted in this study. The results indicate a general trend of the relationships between properties of materials and degrees of haptic invitation based on averaged data. Investigation of individual differences should be examined further.

Chapter 5: Prominent Perceptual Properties of Materials Determine Invited Behavioral Responses In Chapter 5, the author constructed probabilistic relationships between invited touch motions and perceptual responses to materials. Using the constructed relationships, the author then investigated the propositions underlying the mechanism involved in haptic invitation. The first proposition is that the material with a prominent perceptual properties frequently invites human touch responses. Second, the type of prominence determines the type of invited touch response. The author conducted a series of experiments to construct probabilistic relationships. The author evaluated perceptual properties through sensory evaluation and observed human touch responses to materials. The degree of prominence was calculated from the ratings of perceptual properties. The author validated two propositions. Regarding the first proposition, a positive correlation coefficient of 0.53 was observed between the degrees of haptic invitation and textural prominence. Furthermore, the degrees of textural prominence of materials that invited touch responses were higher than those for materials that were not touched. These results support the first proposition as correct. Regarding the second proposition, probabilistic relationships between the invited touch motions and perceptual properties were constructed. These indicated that invited touch motions varied depending on the different types of prominence in perceptual responses. The probabilistic relationships between invited behaviors and perceptual properties could be used to specify physical properties that invite certain hand movements.

Haptic invitation of material may be interpreted as a phenomenon in which the textural prominence of a material encourages a person to touch it. This hypothesis should be further examined in future physiological and psychophysical studies. Examining the mechanism of haptic invitation will lead to a deeper understanding of systems related to human perceptions.

Future Perspectives The developed methods enable us to understand the relationships among several types of responses such as perception, emotion, and behaviors onto surfaces of products. The developed methods will be used in several studies on haptic, visual, and acoustic stimuli. However, the relationships reported in this thesis will not directly useful in other experimental environments. The characteristics of relationships structured by developed methods vary depending on experimental conditions such as materials, methods, participants, and their various backgrounds. Thus, to expand the availability of developed methods, differences in structures should be examined in future studies.

Findings of this study provide a useful guide for the design of a future social system in which a wide variety of sensors may become popular for use in robotics and wearable technology, and in Internet of Things. Manufacturing and marketing may obtain and use several types of information by means of sensors and systems. The number of additional values in manufacturing and marketing will increase, and such values will vary according to individuals. The methodologies developed in this thesis will be capable of designing and understanding entire systems consisting of several design variables which are reciprocally affected, and then such a system will become the technical foundation for a comprehensive management of a wide variety of design elements in manufacturing.

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