What Appeals to Human Touch? Effects of Tactual Factors and Predictability of Textures on Affinity to Textures

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Abstract

For reasons that have not yet been investigated, some textures appeal to human touch. We investigate the relationships between the physical and sensory factors, the predictability of textures, and their appeal to human touch. We conduct sensory evaluation of 24 artificial clay textures, and the results are analyzed using factor analysis. Experimental results identify five sensory factors. We reveal that 70–80% of the textures' appeal to human touch can be described on the basis of the sensory and physical factors. We propose two models involving the predictability of textures. These models, as well as models based on the sensory and physical factors, explain the affinity to textures.

Keywords: sensory evaluation, textural dimension.

1 Introduction

Certain textures and materials that are used on a daily basis appeal to human touch. What appeals to human touch? Well-polished metal surfaces and finely woven clothes are examples of such materials. In addition, the textures whose haptic sensations are unpredictable may appeal to human touch. Some people may feel like touching such textures in order to investigate their haptic sensations. Discovering the reason for this affinity could enable us to design products that attract customers. In this study, we investigate the properties of materials that appeal to human touch.

To the best of our knowledge, human affinity to such materials has not been investigated. We assume that our affinity is related to the physical and sensory characteristics of the textures. In previous studies, tactile sensations were described by the sensory characteristics of textures [1, 2, 3, 4]. Other studies have investigated the relationships between the physical and sensory characteristics of textures [5, 6]. From the viewpoint of product design, Winakor et al. studied the effect of textiles' physical characteristics on customers' preferences [7]. In addition, the relationships between human impressions and the characteristics of some specific materials were investigated. For example, some studies investigated relationships of this nature in regards to wrapping paper [8], sleeping wear [9] and car sheets [10, 11]. Kawabata et al. proposed a method of estimating sensory characteristics from the physical characteristics of clothing fabrics [12]. However, the relationship between the physical and sensory factors of the textures and their appeal to human touch has not been reported thus far.

The present study contains two hypotheses about the appeal to human touch. When we see a texture, our affinity to it is induced by its appearances. Therefore, the physical factors of the textures may directly induce human affinity. On the other hand, the affinity to textures may be determined through human sensory processing. The first hypothesis is that the affinity is attributable to the physical and sensory factors of the textures. In addition, the predictability of textures is potentially related to the affinity. For example, some people may want to touch textures whose haptic sensations are apparently unpredictable. On the other hand, some people may not be interested in such textures. Therefore, the second hypothesis is that the predictability of textures affect the relationships between the affinity to textures and the sensory factors of textures.

We experimentally verify the above-mentioned hypotheses. The objective of this study is to investigate how and to what extent the physical and sensory factors of textures correlate with their appeal to human touch and how and to what extent the predictability of textures affects affinity to textures. This affinity may depend on personal predispositions of participants, but we average individual responses to investigate a potential trend in the relationships between the factors of the textures and their appeal to human touch.

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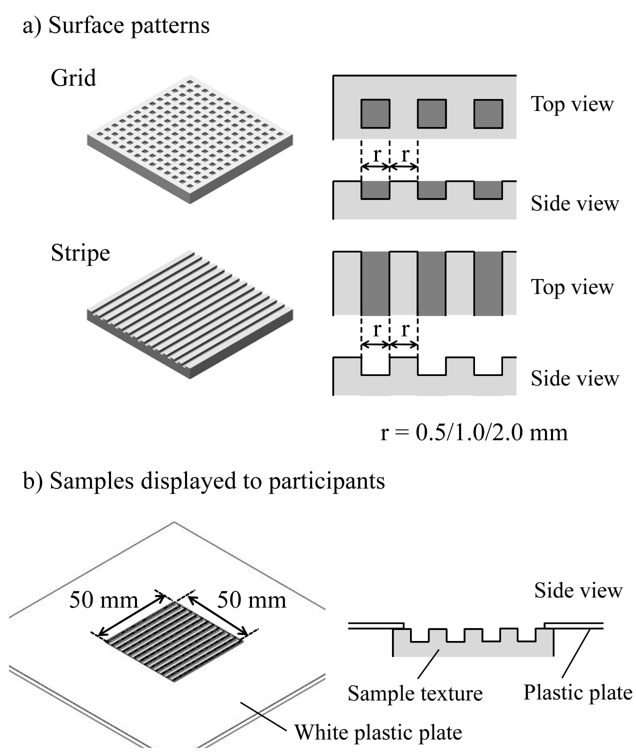

Figure 1: Clay sample textures

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2 Definitions of Appeal to Human Touch

In this study, we assume that the textures' visual appearance contribute to their appeal to human touch. Therefore, in the experiment, participants evaluate textures without touching them. In order to prevent the variations in cultural background from affecting the intensity of the affinity, the sample textures should not be associated with something specific. To this end, in this study, we use simple clay plates with textured surfaces.

The participants rank all the sample textures in the order of the intensity of their affinity to the textures, and we quantitatively assess the intensity of the affinity from the rank. In addition, to avoid variations in the affinity caused by age and gender, participants are limited to males in their twenties. Finally, "touch" does not imply pushing, or holding an object; it simply implies stroking the surface of textures.

3 Stimulation: physical factors of texture

Rather than finely investigating the effect of single physical factor, we are going to see the possible influence of some physical factors. We made 24 different textures controlled by four physical factors: surface colors, surface gloss patterns, surface shape-types, and surface ridge and groove widths. We adopted light clay (Hearty Soft White, PADICO, Tokyo, Japan) as the texture material. The clay was mold into 55.0 mm × 55.0 mm × 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. These colors should 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 for the clay and paints 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, mold, and dried. The JIS specular gloss values of the textures were 2.4%, 94.2%, 1.7%, and 85.1% for the glossless and glossy blue and glossless and glossy orange, respectively. As shown in Fig. 1, two shape types were used: grid 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 × 2 gloss patterns × 2 shape types × 3 ridge and groove widths).

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

4 Experiment

In Task 1, the participants evaluated textures one after the other using the semantic differential (SD) method. Because we used adjective terms that included "predictable-unpredictable" in the experiments, we could quantify sensory properties that included the predictability of the textures. We then applied factor analysis to these properties (excluding "predictable-unpredictable") to obtain the independent sensory factors.

After Task 1, the participants ranked all 24 textures in order of the intensity of their affinity to the textures (Task 2). Based on the ranks of the textures, we calculated the degrees of affinity to each texture. Finally, we investigated the relationships between the degrees of affinity and the physical and sensory factors using multiple regression analyses in section 6, and verified the validity of two models that potentially describe the relationships between the predictability of perceived textures and the degrees of affinity to textures through multiple regression analyses in section 7.

4.1 Task 1: Sensory evaluation of textures

In order to quantify the sensory properties of the textures, we conducted sensory evaluations using the SD method. The participants evaluated the textures using five-point scales in terms of a pair of adjective terms, such as "rough-smooth." The adjective terms used in the experiments were chosen in reference to studies on visual and haptic perception. In the experiments, we provided both English and Japanese terms on the evaluation sheets. We conducted preliminary experiments to remove and merge the candidate terms according to their appropriateness for the textures in this study. For example, we removed the terms whose scores did not vary, such as "thick-thin." Also, we merged adjective terms with similar meanings such as "shiny-matte" and "glossy-dull." In the end, 16 adjective pairs were left, as shown in Table 1.

The participants were voluntary and included 12 students in their twenties from the authors' laboratory. As shown in Fig. 1b, a large white plate with a 50 mm × 50 mm square window was placed on the sample texture so that the participants would see only the textured surfaces and not the sides of the samples. The participants were instructed to attempt to keep their head positions fixed in order to retain the relative position between the head and the texture samples.

The textures and the adjective terms used to sort them were presented to each participant in random order. We conducted experiments in a laboratory environment where the temperature was approximately 24 °C, and the textures were placed under an illumination of approximately 460 lx.

4.2 Factor analysis: Data analysis of Task 1

We assigned values of 1 to 5 on the five-point adjective scales obtained in Task 1. In order to reduce the effects of individual differences in sensory evaluation, the evaluation values of each adjective pairs were normalized within a single participant. Then, they were averaged across all the participants. To decrease the number of variables used in the later analysis, we applied factor analysis to the evaluation 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 term pairs for the texture specified by i. The adjective term pairs were those listed in Table 1 excluding "predictable-unpredictable"; thus, $p = 15$. $\boldsymbol{x}_i$ was broken down into m common factors $\boldsymbol{f}_i$ and unique factors $\boldsymbol{e}_i$:

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

where the factor loadings $\boldsymbol{A}$ explain the strength of the relationships between common factors and adjective terms. n was the number of texture types ($n = 24$). We applied varimax rotation to facilitate interpretation of the relationships between factors and adjective terms.

Table 1: Adjective terms

harsh	-	not harsh	uneven	-	flat
glossy	-	glossless	elegant	-	inelegant
vague	-	clear	dark	-	light
comfortable	-	uncomfortable	soft	-	hard
dry	-	wet	vivid	-	colorless
rough	-	smooth	warm	-	cold
slippery	-	sticky	simple	-	complex
sharp	-	blunt	predictable	-	unpredictable

4.3 Task 2: Texture ranking

After Task 1, all sample textures were simultaneously presented to each participant. The participants ranked the textures in terms of the intensity of their affinity to the textures. Each participant was allowed to give the same rank to a few different textures if he felt that it was difficult to rank all of the textures without any duplicate ranks. Presenting the participants with all 24 different textures at once allowed them to evaluate the relative differences in the textures.

4.4 Normalized-rank approach: Data analysis of Task 2

Because the ranks of the textures are ordinal scales, we converted the ranks to interval scales using the normalized-rank approach [13]. We defined these interval scales as the degrees of affinity. The textures did not include any that might induce intense affinity. Hence, we assumed that the population of degrees followed a normal distribution.

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

$$E(x_{k|n}) = \frac{n!}{(n-k)!(k-1)!} \int_{-\infty}^{\infty} x \cdot a(x) \cdot b(x) \cdot \phi(x) dx \quad (2)$$

$$a(x) = \left[\tfrac{1}{2} - \Phi(x)\right]^{k-1} \quad (3)$$

$$b(x) = \left[\tfrac{1}{2} + \Phi(x)\right]^{n-k} \quad (4)$$

$$\phi(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\tfrac{1}{2}x^2\right) \quad (5)$$

$$\Phi(x) = \int_0^x \phi(z) dz. \quad (6)$$

The degrees of affinity computed for each participant were averaged.

5 RESULTS

5.1 Results of factor analysis: Factor loadings of 15 adjective terms

The factor loadings and each factor's cumulative contributing rates calculated through the factor analysis are shown in Table 2. Cumulative contributing rate is a percentage that represents the degree to which the textures are described by the obtained factors. We adopted the five-factor model ($m = 5$) because the cumulative rate was almost saturated when m was 5. Cells with absolute factor loadings of 0.7 or above are highlighted in gray. Because the adjective terms with large factor loadings represent the property of the factor, we named factor 1 the "glossless, rough, and dry factor," factor 2 the "comfortable and elegant factor," factor 3 the "cold and dark factor," factor 4 the "complex factor," and factor 5 the "uneven factor." Factor 1 was assumed to be affected by the fineness of the surface, which is associated with dryness, glossiness, and slipperiness. In contrast, factor 5 is affected by the coarseness of the surface, which is related to the groove and ridge widths of the surface. As indicated in Table 2, the cumulative contributing rate of the five factors is approximately 0.87; thus, the dimension space of the texture sensations was well established.

Table 2: Results of factor analysis: Factor loadings of 15 adjective terms

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Glossy	−0.940	−0.183	−0.115	0.210	0.024
Dry	0.926	0.250	−0.117	−0.144	0.067
Rough	0.833	−0.152	0.091	0.012	0.159
Slippery	−0.758	0.048	−0.014	0.030	−0.388
Harsh	0.734	0.199	0.109	0.454	−0.259
Comfortable	0.124	0.893	−0.029	0.019	0.231
Elegant	−0.034	0.869	0.026	0.222	−0.015
Sharp	0.214	0.747	0.104	0.480	−0.096
Dark	0.328	−0.028	0.941	0.002	0.009
Cold	−0.197	0.079	0.938	0.136	0.130
Complex	−0.110	0.199	−0.009	0.960	−0.146
Uneven	0.186	0.040	0.121	−0.145	0.903
Soft	0.270	−0.373	−0.523	−0.556	0.210
Vivid	−0.559	0.253	−0.649	0.387	0.065
Vague	−0.014	−0.515	0.087	0.122	−0.574
Contribut. rates	0.279	0.186	0.169	0.132	0.103
Cumulative Contribut. rates	0.279	0.465	0.634	0.767	0.870

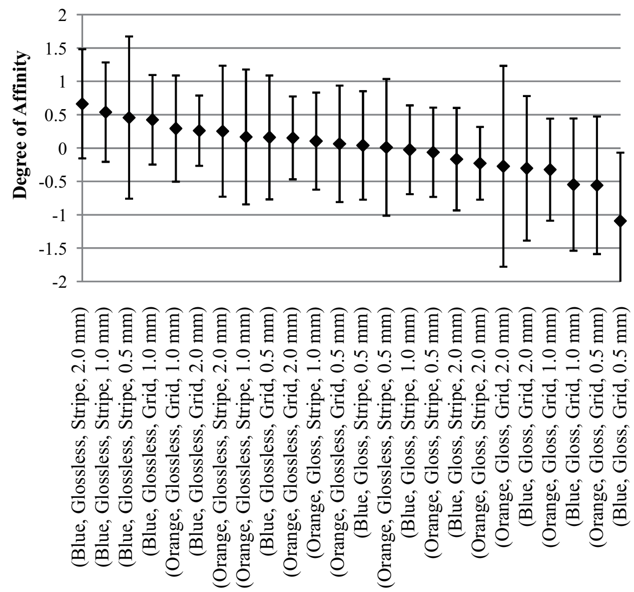

Figure 2: Degrees of affinity to textures

5.2 Degrees of affinity to textures

The degrees of affinity that resulted from Task 2 are shown in Fig. 2. The textures are arranged in descending order of degree. In terms of the surface gloss, the degree of glossless textures was larger than that of glossy textures. The textures with the ten largest degrees are glossless textures. Surface gloss was assumed to affect the degrees much more significantly than the other physical factors. Regarding the effects of the shape type, degrees of striped textures are larger than those of grid textures. Regarding the surface color, the degrees of blue textures are slightly larger than those of orange textures; for the ridge and groove width, degrees slightly increase in proportion to the width. Thus, the glossless blue texture whose shape type is stripe and whose ridge and groove width is 2.0 mm shows the highest degree of affinity. The values of the standard deviations were high, though the degrees of affinity were averaged across all the participants in order to address general trends in this study.

6 Relationships between Degrees of Affinity and Factors of Textures

To investigate the relationships between the degrees of affinity and the factors of the textures, we performed multiple regression analysis. We performed the analysis in two different arrangements: first, objective variables are degrees and explanatory variables are physical factor scores of textures, and second, objective variables are degrees, and explanatory variables are sensory factor scores of textures. Multiple regression analysis was applied to the standardized values. In addition, we obtained the correlation coefficients between the physical and sensory factor scores and attempted to connect both factors using these coefficients.

6.1 Relationships between degrees of affinity and physical factors

We conducted multiple regression analysis with the objective and explanatory variables being the degrees of affinity and physical factor scores of textures, respectively. The standard partial regression coefficients are shown in Table 3. We found a significant negative correlation between the surface gloss and the degrees. In other words, glossiness decreases the degrees of affinity. Next, we determined the correlation between the shape type (stripe/grid) of the textures and the degrees: the degrees for striped textures were greater than the degrees for grid textures.

In contrast, there was little correlation between the degrees and the surface color (blue/orange) or the ridge and groove width (0.5/1.0/2.0 mm). Therefore, we estimated that the degrees of glossless and striped textures are high values. This estimate is consistent with the results shown in Fig. 2. In this case, R^2 was 0.72; therefore, physical factors describe the degrees of affinity as 72% of the variance in the data.

6.2 Relationships between degrees of affinity and sensory factors

We describe the relationships between the degrees of affinity and sensory factor scores of textures ($\boldsymbol{f}_i$) that resulted from factor analysis. We conducted the multiple regression analysis with the objective and explanatory variables being the degrees of affinity and sensory factor scores of textures, respectively. In Table 4, we list the standard partial regression coefficients that resulted from the multiple regression analysis. We found strong correlations between factors 1 (glossless, rough, dry) and 2 (comfortable, elegant) and the degrees of affinity. Slight correlations between factors 4 (complex) and 5 (uneven) and the degrees were also observed. Factor 3 (cold, dark) did not have any effects on the degrees. Thus, textures that were dry, glossless, comfortable, and elegant showed high degrees of affinity. Human affinity to the textures was induced not only by the comfortable factor but also the glossless, rough, dry factors. In this regression analysis, R^2 was 0.78; therefore the sensory factors described the degrees of affinity by 78% of the total. Interestingly, factor 3 is the third factor that contributes to the recognition of textures, though it does not contribute to the degrees. In contrast, factors 4 and 5 are minor factors for texture recognition, but they more strongly influence the degrees of affinity.

Table 3: Regression coefficients of physical factor scores and degrees of affinity

	Color (+:Blue/ -:Orange)	Gloss (+:Glossless/ -:Glossy)	Shape Type (+:Stripe/ -:Grid)	Ridge and groove wid.
Degrees of affinity to textures	0.087	0.741	0.376	0.147

Table 4: Regression coefficients of sensory factor scores and degrees of affinity

	Factor 1 Rough Glossless Dry	Factor 2 Elegant Comfort.	Factor 3 Cold Dark	Factor 4 Complex	Factor 5 Uneven
Degrees of affinity to textures	0.591	0.503	0.069	−0.244	0.318

Table 5: Correlation coefficients between physical and sensory factor scores

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Color	−0.055	0.014	0.971	0.044	0.139
Gloss	0.534	0.258	−0.010	0.053	0.260
Shape type	0.457	0.336	0.093	−0.490	−0.134
R & G width	−0.038	−0.439	−0.018	−0.741	0.408

6.3 Correlations between physical and sensory factors

The correlations between physical and sensory factors are presented in Table 5. Factor 1 (glossless, rough, dry) is related to the surface gloss and shape type. Glossy and striped textures have higher values in terms of factor 1. Factor 2 (comfortable, elegant) is influenced by the shape type and ridge and groove widths; this indicates that striped textures with finer surface patterns are perceived as more comfortable and elegant. The correlations between factor 3 (cold, dark) and the surface color were strong, while the other physical factors had little effect on this factor. Factor 4 (complex) was strongly affected by the ridge and groove widths–smaller widths lead to higher complexity. Also, grid textures tended to be more complex than striped textures. Finally, factor 5 (uneven) was dominantly affected by the ridge and groove widths of the texture surfaces.

Fig. 3 shows the above mentioned relationships between the degrees of affinity and the physical and sensory factors of the textures. The line width represents the strength of the relationships, which corresponds to the absolute values in Tables 3, 4, and 5. Although the figure is limited to the sample textures used in this study, it shows that the relationships between the degrees of affinity and the physical and sensory factors of the textures were quantitatively clarified.

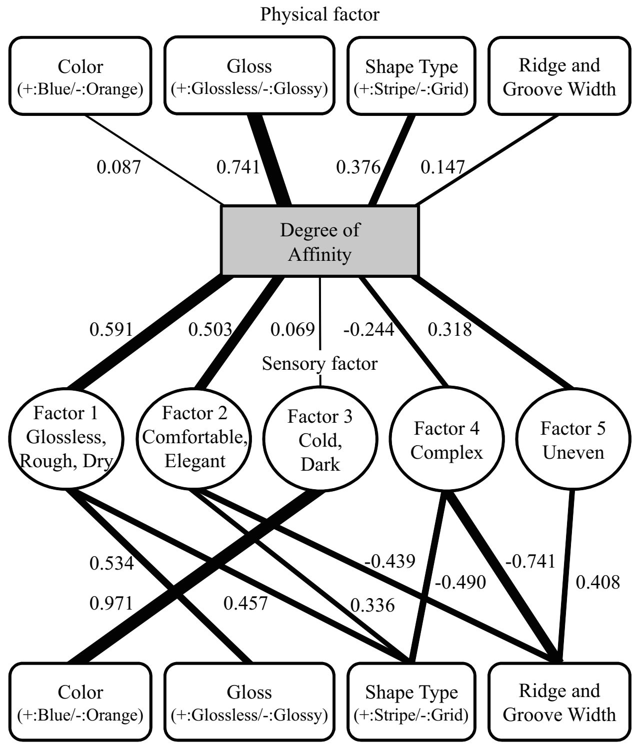

Figure 3: Relationships between sensory factors, physical factors of textures, and degrees of affinity

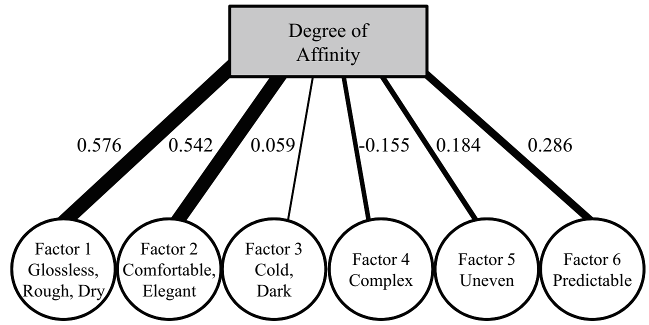

Figure 4: Relationships between factors including predictability and degrees of affinity

7 Two models describing the relationships between predictability of textures and affinity to textures

Here, we investigate how the predictability of texture is related to the affinity to textures. In this study, "predictability" means how predictable the haptic sensations of the textures are from their appearances. We propose the following two models that potentially describe the relationships between the predictability of perceived textures and the degrees of affinity to textures. The participants evaluated the predictability of textures using five-point scales in terms of a "predictable-unpredictable" pair in Task 1 without touching them. We verify the validity of the models through multiple regression analyses.

7.1 First model: Predictability of textures affects each of the other sensory factors

In the first model, the unpredictable textures minimally affect the affinity to textures, whereas the sensory factors of predictable textures strongly affect the degrees of affinity. The first model is

$$\widehat{a_k} = c_1 p_k f_{1k} + c_2 p_k f_{2k} + \cdots + c_5 p_k f_{5k}, \qquad (7)$$

where f_{jk} is the score of factor j for a texture specified by k. Degrees of affinity $\widehat{a}$ are estimated from predictabilities of textures p_k, standard regression coefficients c_j, and sensory factor scores of textures f_{jk}. We assigned values of 1.0 to 0.2 on the five-point adjective scales obtained in Task 1 (1.0 = predictable, 0.2 = unpredictable). In (7), we multiply p and each of the five sensory factor scores of textures f_{jk}. The degrees of affinity to unpredictable textures are reduced almost to zero to counteract the influence of the sensory factor scores on the degrees of affinity. From the multiple regression analysis of (7), R^2 was 0.79. This is as large as that of the model in section 6. We expected R^2 of the model specified in (7) to be higher than that of the model in section 6, but (7) describes the degrees of affinity as well as the model in section 6 does.

7.2 Second model: Predictability of textures is a factor independent of the other sensory factors

In the second model, we assume linear relationships between the predictability of textures and degrees of affinity to textures. The second model is

$$\widehat{a'_k} = c'_1 f'_{1k} + c'_2 f'_{2k} + \cdots + c'_5 f'_{5k} + c'_6 p'_k, \qquad (8)$$

where predictability of textures p'_k affects degrees of affinity to textures as a factor independent of the other five sensory factors of the textures. If c'_6 is positive, the more predictable textures show the higher degrees of affinity. If c'_6 is negative, the degrees of affinity to unpredictable textures are high, meaning that people would like to touch the textures in order to investigate their unpredictable haptic properties. We verified the validity of this model through the multiple regression analysis. Fig. 4 shows the results of the analysis. Values in the figure are the coefficients of the six factors. Factor 6 (predictable) is the third largest factor that contributes to the degrees of affinity. The standard regression coefficient between factor 6 and the degrees of affinity was positive. Therefore, the degrees of affinity to predictable textures were higher than those to unpredictable textures. In this regression analysis, R^2 was 0.83. The model in (8) describes the degrees of affinity as well as the model in section 6 does; R^2 for the model in section 6 was 0.78.

8 Discussions

8.1 Physical and sensory factors of textures effectively described our affinity to the textures

We found that the physical and sensory factors of the textures described the degrees of affinity with accuracies of 72% and 78%, respectively, indicating that these factors effectively describe our affinity to the textures. Although the acquired relationships between the intensity of the affinity and these factors were limited to the sample textures used in this study, the results support the argument that affinity to texture is generally determined by physical and sensory factors. Because the linear combination of the physical factors accounted for 72% of the variations in affinity, the affinity may be intuitively driven by the visual appearances of the textures. On the other hand, the sensory factors describe the affinity as well as the physical factors do, which suggests that our internal sensory evaluation process mediates the affinity. The remaining 20–30% of the variations that these factors could not describe may be due to the physical and adjective terms that this study did not consider. Individual differences in decision criteria in the two experimental tasks may also have contributed to the residuals of the regression analyses.

8.2 Effect of predictability of textures on affinity to textures

In section 7, we constructed two types of models concerning the predictability of textures and their appeal to human touch. These models were constructed based on the model acquired in section 6. Thus, we expected that the models in section 7 would describe the affinity to textures better than section 6 model did. However, in terms of R^2, the models in sections 6 and 7 described the affinity almost equally well.

The R^2 of the models in section 7 were not significantly higher than that of the model in section 6 (contrary to our expectations) for the following reasons: The model described by (7) can not properly account for the textures whose haptic sensations are unpredictable, but its affinity to human touch is significant. On the other hand, the model described by (8) is not suitable for the predictable and unappealing textures.

However, the models in section 7 are not inferior to the model in section 6. The models in section 7 describe the variations of the affinity with an accuracy of 80% that is comparable the model in section 6. Also, according to the results of section 7.2, the predictability possibly influences the affinity of textures, followed by the factors of glossless, rough, dry and comfortable, elegant. Hence, the predictability is an important factor, and it is expected that a novel model that effectively involves the effects of the predictability will elucidate the causes behind texture's appeal to human touch.

9 Conclusions

In this study, we investigated the properties of specified textures that appeal to human touch. To determine the cause of this affinity, we investigated the relationships between the physical and sensory factors, the predictability of the textures, and their appeal to human touch. We used textures in such a way that we were able to control their physical factors. The degrees of affinity were measured by a ranking system and the normalized-rank method. In order to quantify the sensory factors of the textures, we conducted sensory evaluation and factor analysis. Consequently, five sensory factors were identified: glossless, rough, dry; comfortable, elegant; cold, dark; complex; and uneven. Multiple regression analyses revealed that the physical and sensory factors effectively described the degrees of affinity with accuracies of 72% and 78%, respectively. Regarding the physical factors of the textures, their glossiness and surface shape patterns strongly affected the degrees of affinity. Regarding the influence of the sensory factors, glossless, rough, dry, comfortable, and elegant were observed to be strongly related to the degrees.

We constructed two models explaining the relationships between the predictability of the perceived textures and the degrees of affinity. In the first model, the predictability affected the other sensory factors. In the second model, the predictability was a factor independent of the other sensory factors. These models described our affinity to the textures as well as the models that did not include the predictability.

The methodology of this study is useful for determining the best combinations among limited physical factors in terms of texture's appeal to human touch. In product design, limited physical factors are available; hence, the proposed method can enable us to design products or textures– in shops or amusement centers, for example–that appeal to human touch.

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