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Tactile Estimation of Surface Texture Based on Heightmap Image Features and Customer's Attribute Information

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ABSTRACT

In this study, we investigated whether the accuracy of tactile estimation of surface textures can be improved by considering the customer's attribute information. We transformed the texture into a heightmap image and used the image features as input for tactile estimation by machine learning. The results show that the accuracy of tactile estimation is statistically improved by taking into account the gender, risk preference, and personality of the subjects. This method is expected to be useful for designers to adjust products according to the customer and to improve product quality based on tactile sensation.

Keywords: Haptics, Surface texture, Customer attributes

INTRODUCTION

The surface texture of products affects not only the product's appearance and functionality but also the product's haptic sensation. Previous research examined how haptic surface texture affects users' product evaluations, with demonstrations in diverse contexts such as automobile interiors (Yun et al., 2004) and cosmetic case textures (Ritnamkam et al., 2016). The satisfaction derived from such texture is termed Kansei Quality, highlighted as an extra value distinguishing the product from competitors. Product development based on tactile typically follows a design, prototype production, and tactile evaluation sequence, where participants evaluate the product to provide feedback. However, prototyping and conducting tactile evaluation is both time-consuming and costly. Hence, a sensory engineering approach has been suggested to quantitatively estimate tactile sensation from 3D surface texture data during the design phase (Elkharraz et al., 2014).

Nevertheless, its tactile prediction methods and accuracy verification focus on all subjects' average tactile evaluation values, thereby overlooking individual differences in tactile evaluation (Natsume et al., 2019). Effective marketing strategies are developed by segmenting customers based on attribute information to target specific customer groups (Wendell, 1956). Previous research found that varying the tactile sensations of smartphone cases influenced their pricing, revealing a correlation between customer attributes and pricing based on tactile evaluation (Kadoya et al., 2022). Therefore, this study examines whether incorporating subjects' demographics information and personalities can enhance the accuracy of tactile estimation from surface texture data compared to overall average evaluations, with the aim of providing a valuable method for designers to adjust products according to the customer and to improve product quality based on tactile sensation.

CREATION OF TEXTURE SAMPLE

In this study, tactile samples were created using heightmap images. The heightmap image is an image where each pixel represents the height of a specific point on the surface, known as a data format that expresses surface texture shapes. We selected 35 heightmaps from the Pertex heightmap database (Halley, 2012) (see Figure 1). A total of 105 samples were fabricated by creating three different maximum height variations - 100, 200, and 300 μm - from 35 selected heightmaps, using rigid urethane material. The process involved creating silicone molds from the heightmaps, casting them with polyurethane resin, applying acrylic pigments to texture sheets, and attaching them to acrylic boards (see Figure 2). These samples were selected to accommodate experimental time constraints and encompass a diverse range of patterns. The texture samples do not pertain to any specific product, as the aim is to ensure the estimation method's applicability across various products.

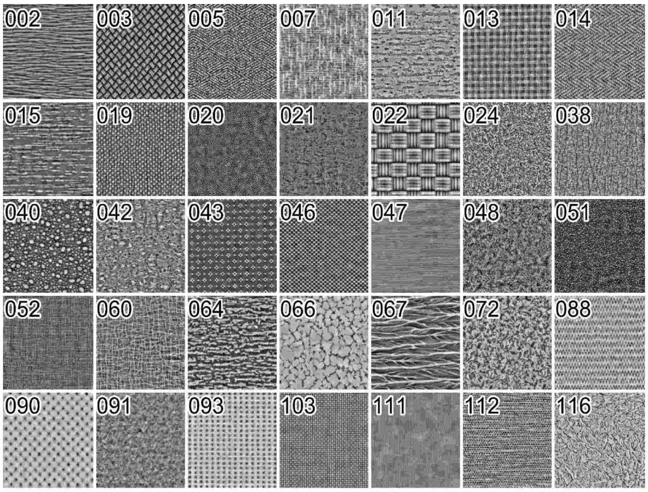

Figure 1: 35 Selected heightmaps.

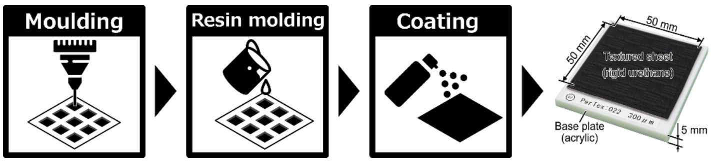

Figure 2: Sample creation methods.

EVALUATION EXPERIMENT

A tactile evaluation experiment was conducted with 16 healthy university students (nine male and seven female), averaging 22.9 ± 1.2 years old. In the evaluation task, participants freely explored the samples with their right index finger and utilized a 7-point Semantic Differential (SD) questionnaire based on six pairs of adjectives on a tablet for evaluation (see Figure 3, 4). An opaque acrylic board was used to eliminate the influence of visual information, and the presentation order was randomized to counteract order effects. Participants also answered a questionnaire covering gender as a demographic attribute, risk preference and personality as a psychological attribute. Personality traits were measured using the TIPI-J questionnaire (Oshio et al., 2012) (see Figure 5), which aims to assess the Big Five personality factors (Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness). These questions (see Table 1) were selected to obtain a wide range of responses from university students, referring to Kadoya's study (Kadoya et al., 2022), which examined the impact of tactile sensations on pricing different smartphone cases and identified attribute information influencing pricing factors from the results.

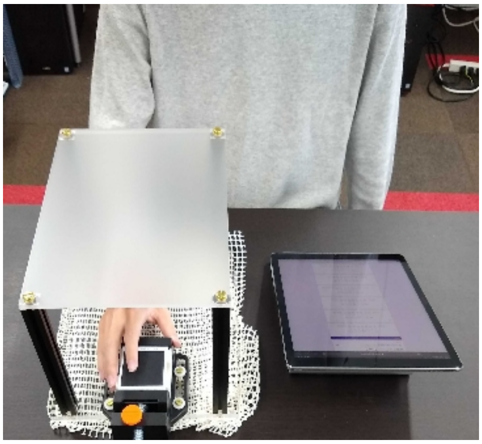

Figure 3: Experimental scene.

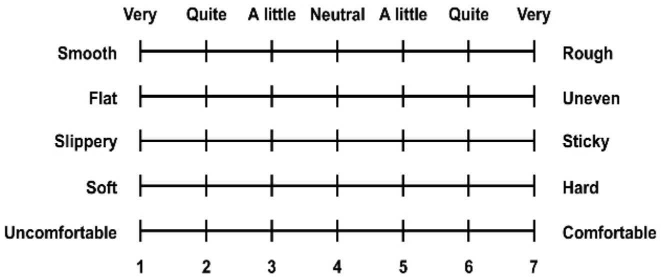

Figure 4: SD questionnaire.

Disagree strongly	Disagree moderately	Disagree a little	Neither agree nor disagree	Agree a little	Agree moderately	Agree strongly
1	2	3	4	5	6	7

I see myself as:

1. _____ Extraverted, enthusiastic.
2. _____ Critical, quarrelsome.
3. _____ Dependable, self-disciplined.
4. _____ Anxious, easily upset.
5. _____ Open to new experiences, complex.
6. _____ Reserved, quiet.
7. _____ Sympathetic, warm.
8. _____ Disorganized, careless.
9. _____ Calm, emotionally stable.
10. _____ Conventional, uncreative.

Figure 5: TIPI (English version) (Gosling, 2003).

Table 1. Attribute information questionnaire.

Category	Item	Question
Statistical Attributes	Gender	Please tell us your gender (Man/Woman).
Psychological Attributes	Risk Preference	When you usually go out, at what percentage of precipitation probability do you decide to bring an umbrella?
	Personality	Japanese version of The Ten-Item Personality Inventory (TIPI-J)

SEGMENTATION

Based on the questionnaire results related to attributes, we determined the criteria for dividing the subjects (see Table 2). Regarding risk preference, as half of the participants answered 50%, we divided them into three segments based on this criterion. For personality, we divided participants into two segments based on the average values of each Big Five trait. To assess the appropriateness of the segments, we calculated Krippendorff's alpha coefficient (Krippendorff, 2011) as inter-rater reliability. Segments with coefficients below 0.2 were excluded from the analysis. The excluded segments are all of Smooth-Rough and some of Soft-Hard, where a slash is drawn in the following table (see Table 4).

Table 2. Definition of each segment.

Category	Segment Variable	Segment
Statistical Attributes	Gender	Man Woman
Psychological Attributes	Risk Preference	Risk Lover : Precipitation Probability > 50% Risk Neutral : Precipitation Probability = 50% Risk Avoidance : Precipitation Probability < 50%
	Personality	[Big Five] - High : Above Average [Big Five] - Low : Below Average

TACTILE ESTIMATION ACCURACY VERIFICATION

We employed the method proposed by Elkharraz (Elkharraz et al., 2014) to create a tactile prediction model. This approach involves scaling the heightmap image to incorporate height information, extracting image features, and predicting tactile sensation using Partial Least Squares Regression (PLSR) to avoid multicollinearity (see Figure 6). The image features used for prediction shown in Table 3, and those definitions follow The Image Biomarker Standardisation Initiative (IBSI). We created models corresponding to each segment and evaluated their accuracy using Nested Leave Sample Out Cross-Validation. We performed parameter tuning through grid search with latent variables 1 to 30 for PLSR. To validate accuracy improvement through segmentation, we compared a conventional model using average tactile evaluations of all participants and a proposed model using only segment-specific subjects data. Mean Squared Error (MSE) served as the accuracy metric. Using the Wilcoxon signed-rank one-sided test, we identified statistically significant differences in the average MSE between the models, suggesting the effectiveness of considering subjects' attributes in tactile prediction (see Table 4). The slashes within the table denote items excluded based on the inter-rater reliability as mentioned above.

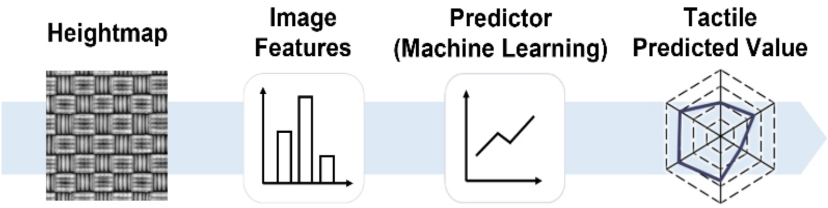

Figure 6: Tactile estimation method.

Table 3. Image features.

Class	Features
First Oder Statistics	Variance Skewness Kurtosis Uniformity Entropy
Second order statics (GLCM features)	Angular second moment (ASM) Contrast Correlation Sum of Squares Inverse difference moment Sum variance Sum entropy Entropy Difference variance Difference entropy

DISCUSSION

The areas indicated by the red asterisks in Table 4 were found to improve the accuracy of tactile prediction by considering their attribute information. We discuss the areas where the effectiveness of the proposed method was remarkable. Considering gender significantly improved accuracy, particularly in assessing the roughness of "Flat-Uneven". In previous studies, differences in tactile evaluation between men and women have been found, and it has been due to the density of neural arrangement caused by differences in hand size between the genders (Peters et al., 2009). Flat-Uneven corresponds to macro-roughness, a sensation felt just by putting a finger on a surface. The fact that we could account for differences in tactile sensation caused by finger size between men and women may have contributed to the improved prediction accuracy in this study. Considering risk preferences significantly improved accuracy, particularly in assessing the sense of friction "Slippery-Sticky". In a previous study (Kadoya et al., 2022), a relationship between risk preference and tactile preference for smartphone cases was found, which was speculated to be due to the frictional sensation being related to the safety of the product by making it easier to hold and harder to drop. Although we did not limit the target products in this study, it is possible that the subjects acquired specific tactile senses based on their risk preferences in their daily lives and that their evaluation of the friction senses was consistent across risk preferences. Personality traits improved prediction accuracy in some items, affirming the validity of segmentation based on the Big Five traits. Previous studies have suggested that extraversion and activity in the primary somatosensory cortex, an area of the cerebral cortex that processes pain and touch, may be involved (Michael, 2012). However, the relationship between personality and haptic perception is largely unexplored. This study found that Conscientiousness, Neuroticism, and Openness improved the prediction accuracy of several tactile adjectives. As a whole, this study helped us to explore new possibilities in the relationship between personality and tactile sensation, which has not been studied much so far, and showed the effectiveness of predicting tactile sensation based on the subject's personality. Though some segment differences do not show up, increasing the number of participants could establish optimal prediction criteria or consider various attribute combinations.

Table 4. Test results.

	Proposed Method Better
$0.005 < p < 0.025$	*
$p < 0.005$	**

(Continued)

Table 4. Continued

Target		Smooth Rough	Flat Uneven	Slippery Sticky	Soft Hard	Uncomfortable Comfortable
Gender	Male		**			
	Female					
Risk Preferences	Lover			*	**	
	Neutral					
	Avoidance			**		
Extraversion	High					
	Low					
Agreeableness	High					
	Low					
Conscientiousness	High		*			
	Low				*	
Neuroticism	High					
	Low			*		
Openness	High					
	Low		**			

CONCLUSION

This study proposed a method for predicting tactile sensations based on the observer's demographic and personality parameters. As a result, it was found that incorporating attribute information into the predictive model improved the accuracy of tactile predictions for some specific adjective items. Based on this study's method, designers can create product designs that cater to individual needs and preferences.

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