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Fingertip Interaction Metrics Correlate with Visual and Haptic Perception of Real Surfaces

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***Abstract*— Both vision and touch contribute to the perception of real surfaces. Although there have been many studies on the individual contributions of each sense, it is still unclear how each modality's information is processed and integrated. To fill this gap, we investigated the similarity of visual and haptic perceptual spaces, as well as how well they each correlate with fingertip interaction metrics. Twenty participants interacted with ten different real surfaces from the Penn Haptic Texture Toolkit by either looking at or touching them and judged their similarity in pairs. By analyzing the resulting similarity ratings using non-metric multi-dimensional scaling (NMDS), we found that surfaces are similarly organized within the three-dimensional perceptual spaces of both modalities. Also, between-participant correlations were significantly higher in the haptic condition. In a separate experiment, we obtained the contact forces and accelerations acting on one finger interacting with each surface in a controlled way. We analyzed the collected fingertip interaction data in both the time and frequency domains. Our results suggest that the three perceptual dimensions for each modality can be represented by roughness/smoothness, hardness/softness, and friction, and that these dimensions can be estimated by surface vibration power, tap spectral centroid, and kinetic friction coefficient, respectively.**

I. Introduction

Both vision and touch play important roles in human perception of real surfaces. Our perceptual evaluations of surfaces can be based on different physical properties (e.g., temperature, roughness, compliance) and are usually enabled by contributions from both modalities [1], [2]. For example, when we consider a piece of clothing in a store, we both look at it and touch it to understand its quality. Although there have been many studies characterizing the information gathered by the individual senses, it is still unclear how each modality's information is processed and integrated [1], [2].

Among the recent studies that have investigated material and surface properties, Bergmann Tiest and Kappers [3] separately compared the perceived roughness of different materials based on visual and haptic cues. They found that both visual and haptic ratings matched well with measurements of the physical roughness of the materials.

Recent studies on multi-sensory surface perception have also considered other material properties. Baumgartner et al. [4] conducted psychophysical experiments in which participants categorized and rated 84 different materials for several material properties. They found that the materials were similarly organized within the perceptual space in both modalities. Their results also revealed that hardness and roughness are the main material characteristics for surface perception in both senses. Adams et al. [5] conducted discrimination experiments using virtual objects that varied in look and feel. They showed that the visual gloss and haptic friction are correlated cues for surface perception.

Scientists have also investigated the similarity of different senses in terms of affective attributes. Fujisaki et al. [6] investigated whether the same affective classifications of materials can be found in vision, audition, and touch, using wood as the target object. Twenty-two different wood types including genuine, processed, and fake wood were perceptually evaluated using a questionnaire consisting of twenty-three items (12 perceptual and 11 affective). The results demonstrated that evaluations of the affective properties of wood were similar in all three modalities. Recently, Drewing et al. [7] investigated the relations between affective and sensory material dimensions in touch. The participants explored 47 solid, fluid, and granular materials and rated them according to sensory and affective attributes. Their results demonstrated that the range of affective responses is broader than researchers previously assumed, and they suggest systematic associations between specific affective and sensory dimensions.

In this study, we compare visual and haptic perception of a variety of real surfaces, similar to [4]. However, instead of asking participants to categorize the surfaces based on specific material properties, we ask them to rate their pairwise similarity by either looking at them or touching them. By analyzing these similarity ratings using MDS, we obtain visual and haptic perceptual spaces. This approach is similar to that taken by Cooke et al., who pioneered the study of parametrically defined objects differing in shape and texture [8]. Their results showed that the participants who judged similarity by vision tended to weight shape more than texture, whereas those judging similarity by touch assigned the weights almost equally.

Following an approach that is unique from [4], we collect contact forces and accelerations from an instrumented fingertip interacting with each surface. By analyzing this data set in physically motivated ways, we calculate three metrics to obtain a physical parameter space. Then we compare this physical space to the visual and haptic perceptual ones. Previous works that investigated the correlation between physical surface properties and cross-modality perceptual judgments focused on only one specific property [3], [5], [9].

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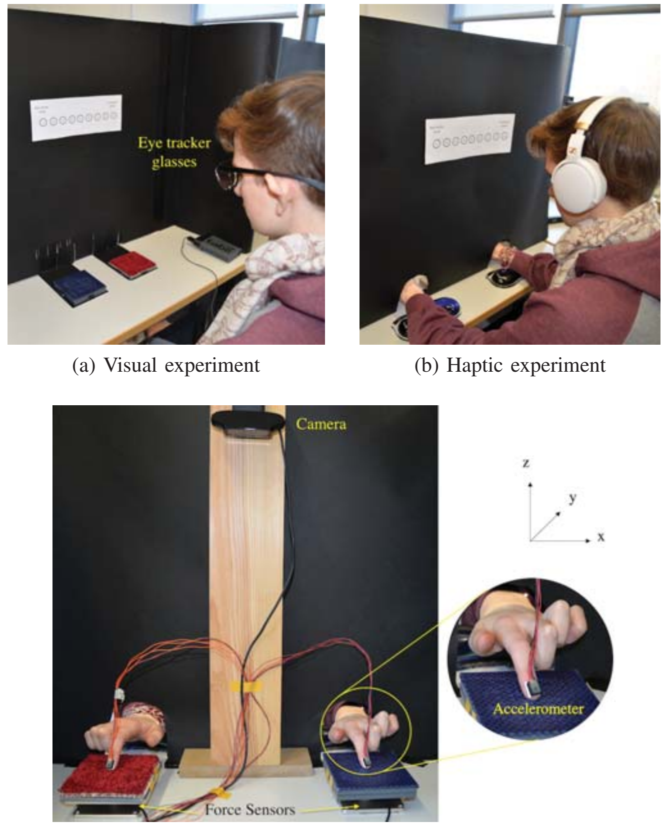
(a) Metail Foil (b) Carpet (c) Cork (d) Floortile (e) Leather (f) Tarp (g) Pink Foam (h) Sandpaper (i) Stone Tile (j) Microfiber Cloth

Fig. 1. The ten surfaces used in the experiments.



(a) Visual experiment (b) Haptic experiment

(c) Instrumentation for haptic experiment

Fig. 2. The experimental setup for the (a) visual and (b-c) haptic experiments. (a) A participant looks at a pair of surfaces without touching. Eye gaze is captured by an eye tracker. (b) A participant touches a pair of surfaces without vision. (c) A force sensor is placed under each surface, and an accelerometer is attached to each of the participant's index fingernails. The scene is recorded from above by a camera.

Moreover, prior studies that correlated physical interaction data with the haptic perception of surfaces collected data from a tool, rather than a fingertip [10], [11].

II. Methods

We conducted two psychophysical experiments and a set of physical measurements. In the first experiment, the participants interacted with the surfaces visually by looking at them. In the second one, the participants touched the surfaces with their index fingers without seeing them. In the physical measurement, we collected fingertip interaction data from the surfaces.

A. Participants

Each psychophysical experiment was conducted with ten participants. Individuals who took part in one experiment did not participate the other one to eliminate cross-modality interactions. Five men and five women with an average age of 30.3 (standard deviation, *SD*: 5.23) did the visual experiment, whereas seven women and three men with an average age of 28.5 (*SD*: 4.14) participated in the haptic version. None of them had current or past visual and sensory-motor disabilities. One left-handed participant took part in the haptic experiment. Only the first author participated in the physical measurements. The experimental procedures were approved by the Ethics Council of the Max Planck Society. All participants gave informed consent. Participants who are not employed by the Max Planck Society were compensated at a rate of 8 EUR per hour.

B. Stimuli

We used ten surfaces from the Penn Haptic Texture Toolkit [12], which is available in our lab. As shown in Fig. 1, the selected surfaces vary in material properties, resulting in a visually and haptically diverse stimulus set. They are also robust to being touched by a human finger. Each surface is a 10.16 cm square and is mounted on a piece of acrylic using double-sided tape. The tape was placed only at the edges of the material so it does not affect the compliance of the surface. The total thickness of each sample (surface plus acrylic plate) is approximately 1.5 cm.

C. Experimental Setup

In the visual experiment, the participant sat in front of two surfaces (see Fig. 2(a)). A black divider was placed between the participant and the experimenter. The divider had two closable holes where the surfaces could be pushed to the participant and pulled back to the experimenter. The participant's gaze was tracked by eye tracker glasses (Tobii Glasses2, Tobii Inc.)

During the haptic experiment, the participant also sat in front of two surfaces. A black divider was placed between the participant and the surfaces, and the participant wore noise cancellation headphones to mask auditory cues (see Fig. 2(b)). These interventions ensured that the participants used only haptic cues during the experiment. Each surface was placed on top of a force sensor (Nano 17 Titanium, ATI Inc.) The contact force vector, contact torque vector, and finger acceleration vector were measured during the experiments as in [13], [14]. The force and torque data were collected by a data acquisition board (PCIe 6323, NI Inc.) with a sampling rate of 10 kHz. Two custom-built digital accelerometer boards (MPU-9250, Invensense

Inc.) were placed on the index fingernails of both hands of the participant (see Fig. 2(c)). The accelerometer data were collected via a micro-controller (ATmega32U4, Atmel Inc.) with a sampling rate of 4 kHz. The scene was recorded from above by a high-resolution camera (C920, Logitech Inc.)

Although we collected participants' fingertip interaction data and eye gaze during the experiments, individual physical interaction data were not analyzed for this paper due to limited space. Instead, in a separate experiment, we collected contact forces and accelerations while an experimenter touched each surface in a consistent manner. This experimental setup was the same as that of the haptic experiment. However, the participant used only her right index finger to explore the surfaces, and her vision was not blocked.

D. Procedure

In both visual and haptic experiments, the participant rated the similarity of pairs of surfaces using a 9-point scale, by either looking at or touching them. All 45 possible pairs of surfaces were presented twice, with each surface in the pair appearing once on the left and once on the right. Each participant observed the pairs in a different random order. Before each experiment, the participants were given instructions and asked to complete a training session. The training session included one very similar pair (stone tile and leather), a very dissimilar pair (metal foil and carpet), and three random pairs. The very similar and dissimilar pairs were selected based on preliminary experimental results. In total there were 95 trials (5 training + (45 pairs $\times$ 2 locations)). Each participant completed the experiments in two sessions separated by a ten-minute break. The duration of the experiment was about 60 and 90 minutes for the visual and haptic experiments respectively.

In the visual experiment, the experimenter prepared each pair behind the divider and then pushed them toward the participant. The participant looked at the surfaces for three seconds, and then the experimenter pulled the surfaces back. Then the participant verbally gave a similarity rating ranging from 1 (completely dissimilar) to 9 (completely similar). The participant was alerted with a sound at the beginning and end of the observation time.

In the haptic experiment, the experimenter placed each surface pair on the force sensors by taping them on the holder at the edges. After this preparation, the participant was alerted with a sound. They then freely explored the two surfaces for 5 seconds using only their index fingers. Then, another sound indicated it was time to remove their fingers from the surfaces. Similar to the visual experiment, they verbally gave a similarity rating from 1 to 9.

In the physical measurements, the participant twice slid her index finger back and forth on the surface laterally with an approximate speed of 50 mm/s. The sliding speed was controlled with a metronome. Each pass started and ended with an alerting sound. After each pass, she removed her finger from the surface and returned it for the next pass. In each pass, the participant applied an average normal force of about 0.3 N (see Fig. 3). These interventions ensured that the data were collected in similar physical conditions.

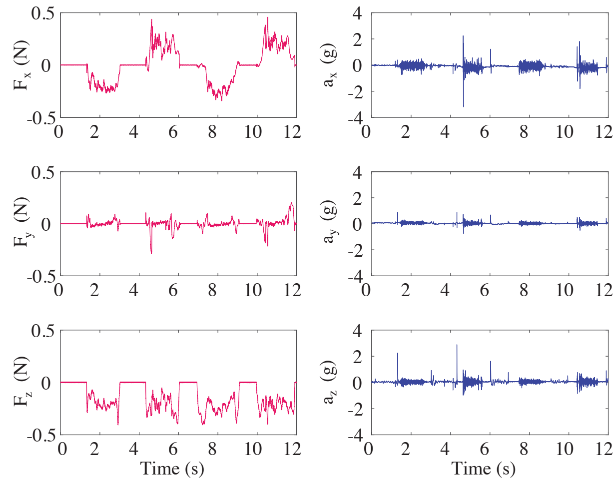


Fig. 3. Example of fingertip contact forces and accelerations collected from the sandpaper surface.

III. Results

The similarity ratings of each participant were converted to normalized dissimilarities by subtracting them from nine and then dividing by eight. For each participant, the Spearman correlations were calculated for the same surface pairs presented in the two possible locations. We used these values to measure the within-participant consistency (see diagonal in Fig. 4). The means of the within-participant correlations were found to be 0.792 (*SD*: 0.102) and 0.839 (*SD*: 0.037) for haptic and visual modalities respectively. These high correlation values show that most participants gave consistent results for the same pairs. An unpaired t-test showed that the within-participant correlations (Fisher z-transformed) of visual and haptic experiments are not significantly different ($p>0.05$). To determine the consistency across participants, we first averaged the dissimilarity data over the two different locations and then correlated these ratings for each participant with those of every other participant (see Fig 4). The means of between-participant correlations were 0.785 (*SD*: 0.062), 0.712 (*SD*: 0.088), and 0.615 (*SD*: 0.11) for haptic-haptic, visual-visual, and haptic-visual respectively. An unpaired t-test analysis revealed that the between-participant correlations (Fisher z-transformed) of visual and haptic experiments significantly differ ($p<0.001$).

Given the high correlations among participants, we next averaged the individual data across participants in the visual and haptic conditions to obtain dissimilarity matrices. Fig. 5 shows a correlation plot in which the average dissimilarity rating for each pair is plotted for the two conditions. As can be seen, the data exhibit a significant correlation (r = 0.814, $p<0.001$). Moreover, the pairs cork–tarp, floortile–tarp, stone tile–tarp, and metal foil–floortile deviate from the others.

After obtaining the two dissimilarity matrices, we performed a non-metric multi-dimensional scaling (NMDS) analysis to calculate perceptual spaces. NMDS typically fits

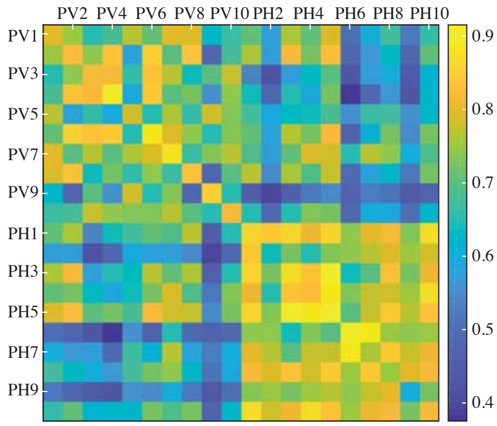


Fig. 4. The within- and between-participant correlations. The within-participant correlations are shown on the diagonal. The first ten columns and rows represent the between-participant correlations for the visual experiments (PV1-PV10), whereas the last ten represent the same for the haptic experiments (PH1-PH10). The rest of the matrix shows between-participant correlations across the two experiments.

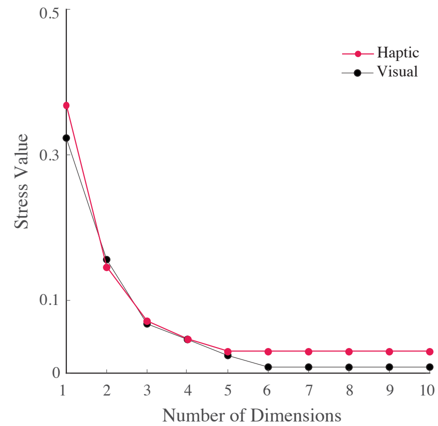


Fig. 6. Stress values calculated by the NMDS analysis of the dissimilarity matrices.

human similarity data better than classical metric MDS, as it uses the ranks of the pairwise distances as input rather than their precise values [8], [15]. We first calculated the stress values for each experiment to understand how many dimensions are needed to explain the data. In MDS studies, the elbow of the stress graph indicates the number of dimensions sufficient to visualize the perceptual space [15], [16]. The elbow appears at three for both modalities (see Fig. 6), so we performed an NMDS analysis for three dimensions. The output of this analysis is the perceptual spaces.

We calculated the physical space using the contact forces and accelerations collected from the third experiment with one participant. Since we obtained two three-dimensional perceptual spaces from the NMDS analysis, we aimed to build a similar physical space. Previous studies provided evidence that the tactile perception of surfaces is dominated mainly by the three dimensions of hardness/softness, roughness/smoothness, and friction (sometimes called stickiness/slipperiness) [10], [17]. Therefore, we formed our physical space based on these dimensions. Following previous work, we used the physical metrics of vibration power during sliding [11], [17], tap spectral centroid [11], [18], and kinetic friction coefficient [11], [14], [17] to estimate the roughness, hardness, and friction of the surfaces, respectively.

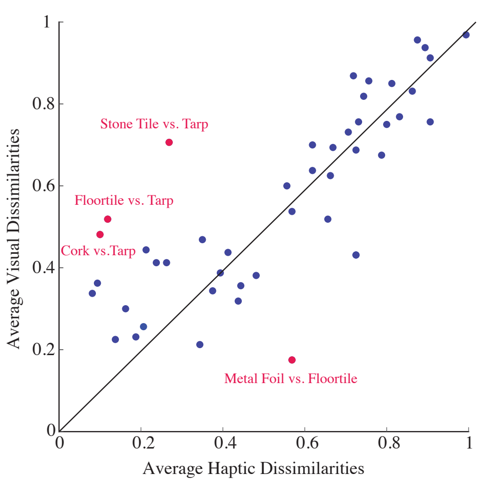


Fig. 5. Average visual dissimilarities versus average haptic dissimilarities. A significant correlation was found ($r = 0.814$ and $p<0.001$). The line represents perfect correlation. The red-marked pairs cork–tarp, floortile–tarp, stone tile–tarp, and metal foil–floortile deviate more from the diagonal than other pairs.

The perceptual roughness of the surfaces is known to increase with the intensity of the vibrations induced during fingertip sliding [17]. We calculated the vibration power from the acceleration signal. We first low-pass filtered these signals with a cut-off frequency of 1 kHz to match human perception. Then, we combined the three-axis acceleration signals into one axis using the discrete Fourier transform (DFT321) [11], [19]. This signal was manually split into four segments, such that each segment represents one finger pass. These four signals were band-pass filtered between 20 Hz and 400 Hz, and then the power spectrum was calculated. The vibration power of the surface was found by summing and averaging these four power spectra.

The hardness of a surface can be discriminated by the vibrations caused by tapping on it. The spectral centroid of this vibration increases with the stiffness of the tapped surface [11]. We calculated the tap spectral centroid from the fingertip acceleration signals in the normal direction. First, these signals were low-pass filtered with a cut-off frequency of 1 kHz. Then, they were segmented into four such that each one represents the first 0.2 seconds of the finger's contact with the surface, which includes a gentle impact. Then, the centroid was calculated from the fast Fourier transform (FFT). The tap spectral centroid of the surface was calculated by averaging these four frequencies.

To represent the perceptual dimension of friction, the kinetic friction coefficient was calculated from the force signals, which were first low-pass filtered with a cut-off frequency of 1 kHz. Then, they were segmented into four in

TABLE I. The calculated friction coefficient, tap spectral centroid, and vibration power for each surface. Note that friction coefficients for finger-surface interactions are frequently larger than one [20].

Surface	**Kinetic Friction Coefficient** (unitless)	**Tapping Centroid** (Hz)	**Vibration Power** (g^2)
Metal Foil	1.697	35.2	0.003
Carpet	0.929	23.7	0.016
Cork	1.070	43.6	0.023
Floortile	1.711	26.7	0.104
Leather	1.021	24.8	0.116
Microfiber Cloth	0.772	35.8	0.006
Pink Foam	0.895	16.4	0.017
Sandpaper	0.973	33.7	0.026
Stone Tile	1.141	68.7	0.104
Tarp	1.049	50.6	0.034

the same way as for vibration power. For each segment, we calculated the kinetic friction coefficient by fitting a Coulomb friction model to the normal and tangential forces. Then these four friction coefficients were averaged for each surface.

The vibration power, tap spectral centroid, and friction coefficient of each surface are reported in Table I. The physical space of the surfaces was formed by calculating the z-scores of their hardness, roughness, and friction values. Then the z-scored perceptual spaces of each modality were fit to the physical space and the other perceptual space using the Procrustes MATLAB function (see Fig. 7 and supplementary video) [4], [15]. This function performs a linear transformation (translation, reflection, and orthogonal rotation) and fits the points of the perceptual space to the points of the physical space. The output of this function also gives a Procrustes value, the distance between the points from one matrix and those from the compared one, reported as the sum of the squared errors. Low output values indicate a better fit. Based on this analysis, the Procrustes values were found as 0.667, 0.614, and 0.443 for the fitting of haptic to physical, visual to physical, and haptic to visual spaces.

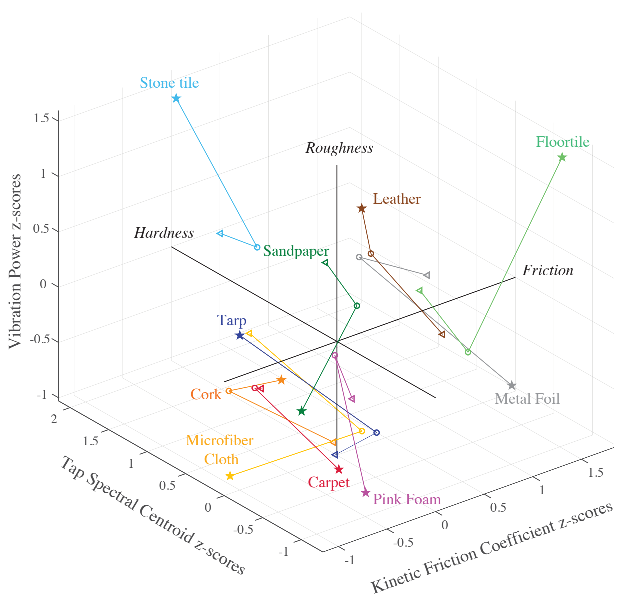


Fig. 7. The perceptual spaces fit to the physical space. The average values of the haptic, visual, and physical data are shown in $\circ$, $\triangleleft$, and $\star$ symbols respectively. The points corresponding to each surface are color coded.

IV. Discussion and Conclusions

Our results suggest that when humans judge real surfaces using either visual or haptic cues, they perceive them similarly. The high correlation between average haptic and visual dissimilarities and the similar organization of the perceptual spaces show that vision and touch rely on congruent perceptual representations (see Figs. 4 and 7). As the determined dimensions (roughness, hardness, and friction) are generally considered more prominent in the haptic modality, touch may be more dominant than vision in surface perception.

Since we used natural surfaces in our experiments, participants may have used their long-term learned bimodal associations to recognize and reason about some textures [21]. Such associations may also explain the divergent pairs in Fig. 5. For example, although metal foil and floortile have very different roughness values, both of them seem polished, which may have caused a misjudgment during the visual similarity task. Also, most participants reported that tarp looked like a fabric, although it is actually plastic; this visual confusion may explain why the pairs cork–tarp, floortile–tarp, and stone tile–tarp have rather different visual and haptic dissimilarity values.

Previously, Baumgartner et al. also obtained similar results [4]. However, they found the three main perceptual dimensions as roughness/smoothness, hardness/softness, and glossiness. The discrepancy of the third dimension may be caused by the difference between the experimental methods [22]. In [4], the participants rated the surfaces based on predefined material properties. Also the same participants did both the visual and haptic experiments in balanced order. In our case, the participants rated the surfaces based on their pairwise similarity and took part in only one condition. Nonetheless, the selected surfaces [22] and participant-to-participant variability [9] may also have significantly affected the results of our study.

We found that the perceptual data of each modality can be localized in a physical space spanned by the metrics of surface vibration power, tap spectral centroid, and kinetic friction. Crucially, here we measured these properties by means of fingertip interaction metrics instead of the tooltips used by other researchers [10], [11]. Although the surfaces and their calculated metrics do not have a one-to-one match, they are located nearby (see Fig. 7 and supplementary video). This mismatch could mainly be caused by the limitations our selected physical metrics have in representing perceptual judgments. For example, we estimated roughness by calculating the power of the vibrations that occur on the fingernail. However, this signal may not be enough to represent the roughness dimension. In fact, it has been shown that roughness can be divided into macro and micro domains

[22]–[24]. Many neurophysiology studies have shown that these two perceptual domains are enabled by different neural mechanisms [22], [25]–[27]. Macro-roughness depends on how slowly adapting mechanoreceptors respond to the spatial distribution of the stimulus. Conversely, micro-roughness stems from the fast adapting mechanoreceptors' response to skin vibration. The presence of hard backing boards may also affect sensor data, although it should also influence similarity ratings accordingly. Other factors that may affect the resulting metrics are differences in the fingertip properties and exploratory behaviors of the participants, as well as varying experimental conditions. For instance, the friction coefficient highly depends on finger moisture and sliding speed [20]. Since we collected physical data from only one participant with a controlled sliding speed, our metrics may deviate from the perceptual results. To better interpret the perceptual spaces, we plan to expand our physical metrics and analyze individual fingertip interaction data in our future work.

The significant difference in between-participant correlation across modalities suggests that vision-specific dimensions such as glossiness, contrast, or color also a play role in surface perception [22]. This finding also supports the hypothesis that vision and touch contribute to surface perception in an independent but complementary manner [1].

To the best of our knowledge, this is the first detailed study investigating the correlation between fingertip interaction data and visual and haptic perception of real surfaces. We believe that our novel experimental setup (which can record how participants visually and haptically interact with surfaces) can enable novel insights into commonalities and differences in the mechanics and dynamics of multi-sensory exploration. Our findings may help us understand not only the individual contributions of each sense but also how information from both senses is integrated and processed. Moreover, our work may help engineers develop new interfaces that visually and haptically display realistic textures.

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