

Alternatives to Friction Coefficient: Fine Touch Perception Relies on Frictional Instabilities

Reviewed Preprint

v1 • February 26, 2025

Not revised

Maryanne Derkaloustian, Pushpita Bhattacharyya, Truc Ngo, Joshua GA Cashaback, Jared Medina, Charles B Dhong 

Department of Materials Science and Engineering, University of Delaware, Newark, United States • Department of Psychological and Brain Sciences, University of Delaware, Newark, United States • Department of Biomedical Engineering, University of Delaware, Newark, United States • Department of Psychology, Emory University, Atlanta, United States

 https://en.wikipedia.org/wiki/Open_access

 Copyright information

eLife Assessment

This **useful** study integrates experimental methods from materials science with psychophysical methods to investigate how frictional stabilities influence tactile surface discrimination. The authors argue that force fluctuations arising from transitions between frictional sliding conditions facilitate the discrimination of surfaces with similar friction coefficients. However, the reliance on friction data obtained from an artificial finger, together with the ambiguous correlative analyses relating these measurements to human psychophysics, renders the findings **incomplete**.

<https://doi.org/10.7554/eLife.104543.1.sa4>

Abstract

Fine touch perception is often correlated to material properties and friction coefficients, but the inherent variability of human motion has led to low correlations and contradictory findings. Instead, we hypothesized that humans use frictional instabilities to discriminate between objects. We constructed a set of coated surfaces with physical differences which were imperceptible by touch but created different types of instabilities based on how quickly a finger is slid and how hard a human finger is pressed during sliding. We found that participant accuracy in tactile discrimination most strongly correlated with formations of steady sliding, and response times negatively correlated with stiction spikes. Conversely, traditional metrics like surface roughness or average friction coefficient did not predict tactile discriminability. Identifying the central role of frictional instabilities as an alternative to using friction coefficients should accelerate the design of tactile interfaces for psychophysics and haptics.

Introduction and Background

People can readily distinguish and describe a variety of textures by touch, but there is no single material parameter or property that consistently predicts human fine touch. Fine touch arises from the friction generated between a finger and an object, so the most common method to classify objects in fine touch is by assigning a constant friction coefficient to different materials.^{1,2} Although the friction coefficient is often convenient, it is not a material property³ and most findings have yielded either contradictory results or low statistical correlations to human performance, like discriminability or identification.^{4,5} The cause of these discrepant findings is, in part, that sliding friction in soft systems have significant oscillations in forces arising from microscale stick-slip, adhesion, and elasticity.⁶ Indeed, the inherent human variability in finger velocity and pressure means that the variations in friction encountered on a single object can be larger than the variations in friction between two distinct objects.^{7–9} Thus, the question we set to answer here is: how can humans rapidly distinguish objects despite inherent human variability in finger motion and resulting friction?

Instead of a material property or parameter, we hypothesized that humans could tell surfaces apart due to the likelihood of encountering frictional instabilities like stiction spikes and slow friction waves. These frictional instabilities arise due to the competition between the elasticity of the finger and adhesion to a substrate.⁶ In an experimental parameter space of finger pressure and velocity, the boundary where one instability type forms versus another is dependent upon surface composition.^{8,10} We surmise that humans actively explore surfaces to find these transitions between different types of frictional instabilities to tell surfaces apart. Classifying surfaces based on transitions between instabilities would be advantageous because it is less variable than raw friction forces typically seen in macroscopic experiments.¹⁰

Most friction at solid interfaces is characterized by some degree of stick-slip behavior, where the fluctuations in force can largely depend upon sliding conditions as well as the material properties of each object.^{11,12} In elastic, rigid systems, a critical spring constant dictated by sliding conditions and slip history can determine whether steady sliding or different forms of slip instabilities occur.^{11,13} These rate and state laws gain even more complexity when one object is soft and deformable, and also makes adhesive contact with a hard surface. Prior to any slip events, the effects of contact aging are amplified with significant intermolecular forces at the interface,¹⁴ and the drastic evolution of contact area while sliding largely controls the resulting friction force.¹⁵ Additionally, local tensile and compressive stresses can often create periodic oscillations in this force, even in the absence of mesoscale interface detachment.¹⁶ These phenomena are sufficiently explained for controlled systems with a constant normal load and known initial conditions, but the dynamics arising from the unconstrained nature of human touch and their mechanistic origins can be more difficult to predict.

Due to these systematic variations in friction, deriving relationships between a constant or average friction coefficient and tactile perception has led to low correlations or findings that do not generalize between studies. Typically, psychophysical studies using this approach rely on combining friction coefficients with other material properties and tactile dimensions defined by qualitative descriptors to extract correlations to participants' ability to distinguish between surfaces.^{4,17} Instead, more direct correlations have often emerged from studies investigating dynamic friction during touch.^{18,19} Gueorguiev *et al.*²⁰ identify a partial slip region, where a finger's peripheral contact area begins to drop until a threshold of smoother sliding, as a strong tactile cue in discriminating between glass and PMMA slabs. However, the connections between their significant differences in physiochemical properties and their stick-slip behavior at the mesoscale remain unclear as these partial slips are dependent on finger velocity and pressure, and human fingers vary in both during free exploration.

Here, we investigate dynamic friction as a predictor across controlled surfaces to establish structure-dynamics-property relationships connecting molecular scale phenomena to mesoscale mechanics and elucidate fine touch perception. Within the ranges of applied finger pressures and sliding velocities observed in humans, the same material can exhibit multiple variations of stick-slip phenomena,^{7,8,21} which challenges correlations derived from singular measurements of tangential force.

Materials and Methods

Surface Preparation

Silane coatings were prepared via chemical vapor deposition (CVD) onto 10 cm-diameter silicon wafers (University Wafer). Clean wafers were first treated with oxygen plasma (Glow Research Glow Plasma System) for 1 minute. They were immediately moved to a desiccator containing ~50 μ L of silane (Gelest, 95-100% purity) on a glass slide. Alkylsilanes and aminosilanes each required a separate desiccator. After pulling vacuum, each desiccator was held under static vacuum for at least 4 hours. Evidence of plasma treatment as well as deposition was confirmed with atomic force microscopy (AFM), x-ray photoelectric spectroscopy (XPS), and contact angle hysteresis experiments (results in **Table 1** and SI).

Atomic Force Microscopy

1×1 cm wafer pieces were imaged with a Bruker Multimode AFM to compare surface profiles of all silanes as well as the effects of plasma treatment. 10×10 μ m scans were generated under tapping mode at a frequency of 1 Hz with tips of a ~120 kHz resonant frequency, and analyzed with Gwyddion microscopy data analysis and visualization software. All height profiles were processed with a third-order background subtraction, a median height correction along the fast scanning (x) axis, and horizontal stroke correction prior to analysis. Aggregates were not masked as they only negligibly changed power spectral density profiles.

X-Ray Photoelectric Spectroscopy

To identify the elements present on our surfaces, 1×1 cm samples were scanned with a Thermo Scientific K-Alpha XPS system. 400 μ m points were scanned on each sample, for individual elements C, N, O, and Cl, as well as an XPS survey scan.

Water Contact Angle Hysteresis

Advancing and receding angles of water droplets on our surfaces were measured using a goniometer (DSA14 Drop Shape Analysis System, Kruss). To measure advancing angles, ~3 μ L of DI water was dispensed onto each surface, and an image of the droplet-surface interface was captured. ~1 μ L of water was then slowly removed from the droplet such that it would recede, when another image was captured. Each droplet was fit to an automatic circle fit in ImageJ to obtain advancing and receding angles. This was repeated five times for each surface, in order to obtain average angles, and average hysteresis by subtracting the two.

Mock Finger Preparation

Friction forces across all six surfaces were measured using a custom apparatus with a polydimethylsiloxane (PDMS, Dow Sylgard 184) mock finger that mimics a human finger's mechanical properties and contact mechanics while exploring a surface relatively closely.^{7,8} PDMS and crosslinker were combined in a 30:1 ratio to achieve a stiffness of 100 kPa comparable to a real finger,²³ then degassed in a vacuum desiccator. The prepared PDMS was then poured into a 1×1×5 cm mold also containing an acrylic 3D-printed "bone" to attach applied masses on top

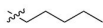
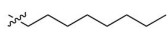
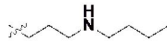
Sample	Surface Structure	Average Roughness (R_a , pm)	Contact Angle ($^{\circ}$)	Average Friction Coefficient ($\bar{\mu}$)	Hurst exponent (H)
C4		861	$(99.06-103.74) \pm 2.5$	2.21	0.56
C5		443	$(100.18-109.68) \pm 2.6$	2.45	0.22
C6		858	$(102.42-109.10) \pm 5.1$	2.49	0.29
C8		431	$(108.38-114.32) \pm 4.0$	3.04	0.06
C4-APTMS		358	$(54.74-59.44) \pm 3.9$	2.06	0.04
APTMS		280	$(49.80-58.28) \pm 5.7$	2.03	0.15

Table 1.

Surface characterization of silanized silicon wafers.

of the “fingertip” area contacting a surface during friction testing. The bone also aids in maintaining the mechanical contributions of the distal phalange around soft tissue.^{7,8} After crosslinking in the mold at 60°C for 1 hour, the finger was treated with UV-Ozone for 8 hours out of the mold to minimize viscoelastic tack.

Mechanical Testing

A custom device using our PDMS mock finger was used to collect macroscopic friction force traces replicating human exploration.^{7,8} After placing a sample surface on a stage, the finger was lowered at a slight angle such that an initial 1 cm² square of “fingertip” contact area could be established. While this shape is not entirely representative of a human finger with curves and ridges, human fingers flatten out enough to reduce the effects of curvature with even very light pressures.^{23–25} This implies that regardless of finger pressure, the contact area is largely load-independent, which is more accurately replicated with a rectangular mock finger. This insensitivity was critical considering the broad range of applied masses ($M = 0, 25, 75$, and 100 g) added onto the deadweight of the finger (6 g) while sliding. The other side of the sensor was connected to a motorized stage (V-508 PIMag Precision Linear Stage, Physikinstrumente) to control both displacement (4 mm across all conditions) and sliding velocity ($v = 5, 10, 25$, and 45 mm s⁻¹). Forces were measured at all 16 combinations of mass and velocity via a 250 g Futek force sensor ($k = 13.9 \text{ N m}^{-1}$) threaded to the bone, and recorded at an average sampling rate of 550 Hz with a Keithley 7510 DMM digitized multimeter. Force traces were collected in sets of 4 slides, discarding the first due to contact aging. Because some mass-velocity combinations were near the boundaries of instability phase transitions, not all force traces at these given conditions exhibited similar profiles. Thus, three sets were collected on fresh spots for each condition to observe enough occurrences of multiple instabilities, at a total of nine traces per combination for each surface.

Instability Classification

Without any previously defined classifications of the instabilities in our systems, we restricted our force traces to 3 main types discussed in the main text: steady sliding, slow frictional waves, or stiction spikes. However, some stiction spikes were not immediately categorizable by eye, as performed independently by two coauthors, but consistency was maintained depending on whether these spikes were followed by steady sliding or slow frictional waves.

Pair Selection for Human Testing

With nine friction force traces for each mass-velocity pair and surface, large frequencies of instabilities could be counted and used to generate instability phase maps for each material. Frequencies of occurrence of steady sliding, stiction spikes, and slow frictional waves on each surface were determined manually, as well as total incidence of instabilities. These frequencies corresponded to color intensities for each instability on the phase maps, revealing similar zones but different boundaries for every surface.

The differences between these frequencies were calculated for several pairs, both previously tested and new pairs. Six pairs with a wide range of differences in total instabilities were selected, three of which had been tested prior to this work. These pairs had different ranges of individual instability differences as well, as shown in **Table 2**.

Human Testing

To verify that the differences in instabilities aid in tactile discrimination, we performed three-alternative forced choice tests (3-AFC) ($N = 10$ participants, $n = 600$ trials) on 10 sighted adult participants (IRB approval in Acknowledgments). In each trial, subjects were presented with three surfaces lined up horizontally to touch, two having the same silane coating and an odd sample out. Pairs as well as unique sample placement were randomized across all subjects and trials. No

Label	Sample Comparison	ΔSS (%)	ΔSFW (%)	ΔSp (%)
<i>P1</i>	C4 vs C4-APTMS	13.9	11.1	2.78
<i>P2</i>	C6 vs C4-APTMS	6.25	18.8	9.72
<i>P3</i>	C4 vs C5	7.64	14.6	9.72
<i>P4</i>	C8 vs C4-APTMS	9.72	23.6	1.39
<i>P5</i>	C4 vs APTMS	16.7	11.1	5.56
<i>P6</i>	C5 vs C4-APTMS	21.5	16.0	12.5

Table 2.

Pairs of samples for human testing by their frequency of instability formation.

blindfolds or visual barriers were used since the appearances of all coatings were the same. Participants could touch for as long as they wanted, but were asked to only use vertical, downward motions with their dominant index fingers to better mimic the conditions for instability formation during mechanical testing with the mock finger. Once a participant made a final decision on which sample was unlike the other two, we input their answer in a premade Qualtrics form which recorded the time to the last click as the response time.

Results and Discussion

Generating Phase Maps of Frictional Instabilities

To test the hypothesis that humans use frictional instabilities to form tactile judgements, we constructed “minimal” tactile surfaces made from the vapor deposition of silanes onto silicon wafers for human testing (Table 1).

We describe these samples as “minimal” because the physical variations in roughness are below the human limits of detection^{22,26} and the bulk and thermal properties of all samples are identical at the human scale because the silanes form a thin layer of order nanometers thickness.^{27,28} Thus the only present differences in these samples are from those in surface chemistry (Table 1, see SI for details). We propose that the role of these differences in surface chemistry is to shift the boundaries between frictional instabilities to different finger pressures and velocities. As there is no existing method to accurately predict phase maps of instabilities of elastic bodies from molecular structure, we experimentally determined these frictional instability maps through a mechanical apparatus with a mock finger (Fig. 1, details in Materials and Methods).

Across the six different surface coatings and 16 different combinations of finger sliding velocity and applied mass, we observed that the friction traces could be categorized into three broad phases, which conceptually originate from the competition between the adhesion and elasticity of the finger. The first phase, *steady sliding* (SS, orange in Fig. 1B), shows a nearly constant friction force, except for high-frequency mechanical oscillations.^{24,29} Mechanistically, this represents sufficient dissipation of kinetic energy relative to driving velocity, thus there is a lack of macroscale or concerted stick-events that lead to large oscillations in force.^{20,24} Instead, microscale stick-slip events result in a high frequency, but small, oscillation around a comparatively steady mean. We observe that this occurs primarily at low applied masses, but different velocity zones depending on the surface. The initial slope in the steady sliding regime, and in all other phases is equal to k_{finger} . The second phase, *slow frictional waves* (SFW, blue in Fig. 1B), manifest as large oscillations in friction force with frequencies lower than any representative timescale for microscopic stick-slip or motor velocity. These oscillations are much larger than electronic noise of ~ 0.04 N. Slow frictional waves represent a scenario where kinetic energy by friction and adhesion is not dissipated sufficiently quick. Instead, stresses within the mock finger can localize to form instabilities like buckling,³⁰ pulses,³¹ or wrinkling³² to relieve the buildup of elastic stresses. We observe that slow frictional waves occurred more frequently at higher masses and velocities compared to steady sliding. This is expected because higher normal loads increase the tangential forces required for motion, and the higher velocities give shorter times to resolve stress irregularities.³³ We also observed a third phase, a singular *stiction spike* (Sp, green in Fig. 1B), that precedes an otherwise smooth, or if also exhibiting a slow frictional wave, comparatively small oscillating trace. This stiction spike represents where the initial barrier to motion, adhesion, represents a significant threshold above the mean sliding friction,³⁴ likely because most of these microscale contacts are broken within a short interval. Stiction spikes were routinely observed even after we discarded the first pull out of a sequential series of four pulls to remove the influence of contact aging originating from setup preparation. Stiction spikes are not necessarily mutually exclusive to steady sliding and slow frictional waves

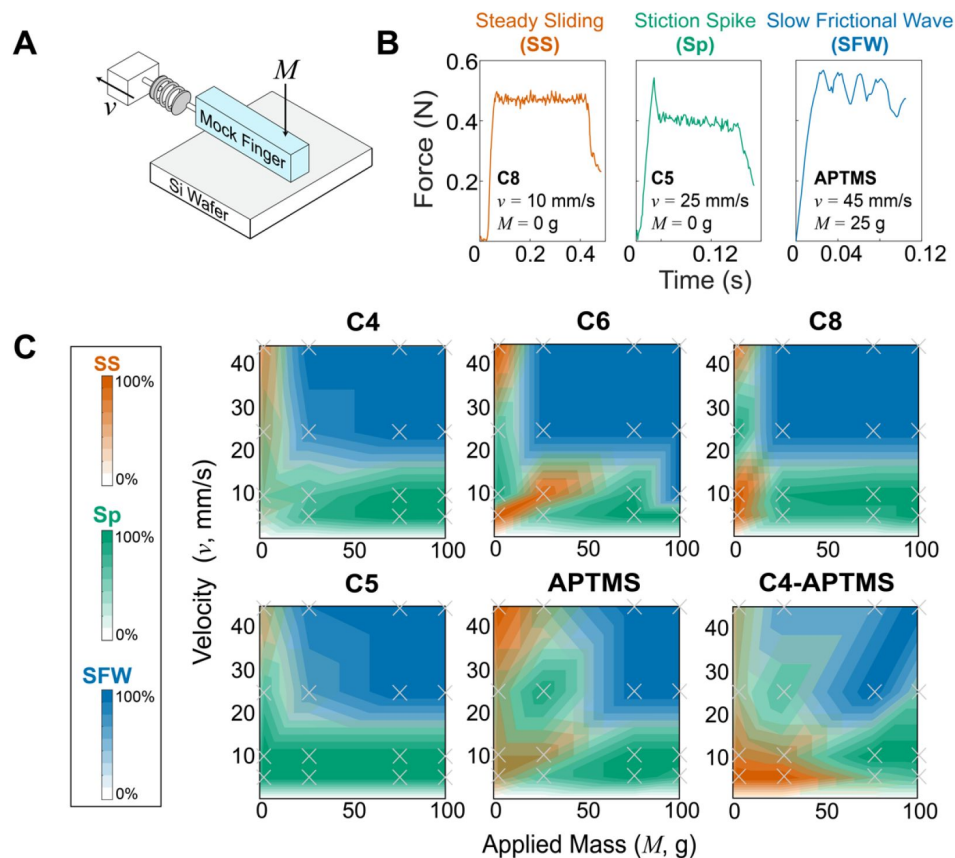


Fig. 1.

Mechanical testing and determination of frictional instability landscape in samples.

A) Schematic of friction testing apparatus. An elastomeric mock finger is connected to a force sensor and motorized stage. The mock finger was driven at four different driving velocities ($v = 5\text{--}45\text{ mm/s}$) at four different applied masses ($M = 0\text{--}100\text{ g}$, in addition to the deadweight of the mock finger), mimicking human exploration. B) Representative force curves of three types of frictional instabilities. *Steady sliding*, (**SS**, orange) shows no distinctive feature besides high frequency force oscillations due to stick-slip, which is above the electronic sensor noise. *Slow frictional waves* (**SFW**, blue) are slower, large amplitude oscillations corresponding to global or coherent stick-slip of the entire mock finger. *Stiction spike* (**Sp**, green) is where a single, large-magnitude stick-slip event is observed at the onset of steady sliding. C) Phase maps of frictional instabilities across all surfaces. Colors and intensities correspond to the type and frequency of each instability respectively at a given condition. Color map created by linear interpolation between experimental conditions, with location of conditions tested indicated by gray ($\times$) marks.

and can coexist with the others (see Fig. S4 of SI). However, based on our heuristic classification scheme, a 10% higher spike than the mean during steady sliding was considered a stiction spike trace. When the spike was followed by slow frictional waves, the traces with the first peak being 40% higher in amplitude were also classified as stiction spikes.

In many cases, we observed that several trials in the same conditions consistently led to mixed phases, despite initially assuming that these originated from experimental error. Upon construction of the phase maps, we saw that mixed phases occur predominantly at boundaries. Conversely, in the interior, we see higher consistency (darker shade). Generally, we see that steady sliding is less frequent in short chained, unaligned surfaces like **C4** and **C5** (see Hurst exponents in **Table 1**). Although no analytical modeling of soft, mesoscale friction analysis has provided accurate phase maps of these instabilities, theoretical work¹⁰ by Putelat *et. al.* and experimental work by others^{16,35} have shown that these instability phase maps can have abrupt transitions.

Human participants testing

The results from **Fig. 1** demonstrate that we can design human experiments with different pairs of surfaces with differential frequencies in the occurrence of instabilities. To determine if humans can detect these three different instabilities, we selected six pairs of surfaces to create a broad range of potential instabilities present across all three types. These are summarized in **Table 2**. The percentages are determined by, in an example, **C4** has steady sliding in 23 out of 144 mechanical pulls and **C4-APTMS** has steady sliding occurring in 43 pulls. Thus, when comparing **C4** versus **C4-APTMS**, they have a difference in steady sliding of 20 out of a maximum 144 pulls, for a ΔSS of 13.9%.

10 participants were asked to perform a three alternative-forced choice task (3-AFC, $n = 600$ total trials), where they are given three samples at a time, two of which have the same surface coating, and one of which has a different coating — the identity and placement of the “odd-man out” sample was randomized. Participants were asked to select which of the one coating is unlike the other, which is advantageous because participants were not prompted to select based on potentially subjective percepts, such as which one feels “smoother” or “rougher”³⁶. To prevent confounding effects from fouling,³⁷ all samples were used only a single time. Blindfolds were unnecessary as all samples are visually identical. Additional testing details are provided in Materials and Methods.

Participants were successful in distinguishing between all pairs (**Fig. 2A**), with all average accuracies above chance (33%, $p < 0.005$ by one-sample *t*-test). There were statistically significant differences in performance across some pairs ($p < 0.05$, Wilcoxon rank sums) as indicated in **Fig. 2A**. Pairs which had similar accuracies are still insightful: as a conceptual example, participants had nearly the same accuracy with **P1** and **P6**, but from **Table 2**, **P1** had small differences (2.78%) in stiction spike production, whereas **P6** had large differences (12.50%).

We used the differential frequencies of each instability in **Table 2** to perform a statistical fit of participant results by using a generalized linear mixed model (GLMM, details in SI). Considering all instabilities individually, we found that only steady sliding was a positive, statistically significant predictor. ($R^2 = 0.38$, $p < 0.05$, shown in **Fig. 2B**). A positive correlation means that the more differences in steady sliding formation between a pair of material leads to higher accuracy in discrimination. Multi-term models including multiple instabilities were not statistically significant. Furthermore, a model accounting for slow frictional waves alone specifically shows a significant, negative effect on performance ($p < 0.01$), suggesting that in these samples and task, the type of instability was not as important. Thus, forming either type of instability (slow frictional waves or stiction spikes) on one surface compared to another surface which consistently generates steady sliding will lead to two surfaces feeling very distinctive.

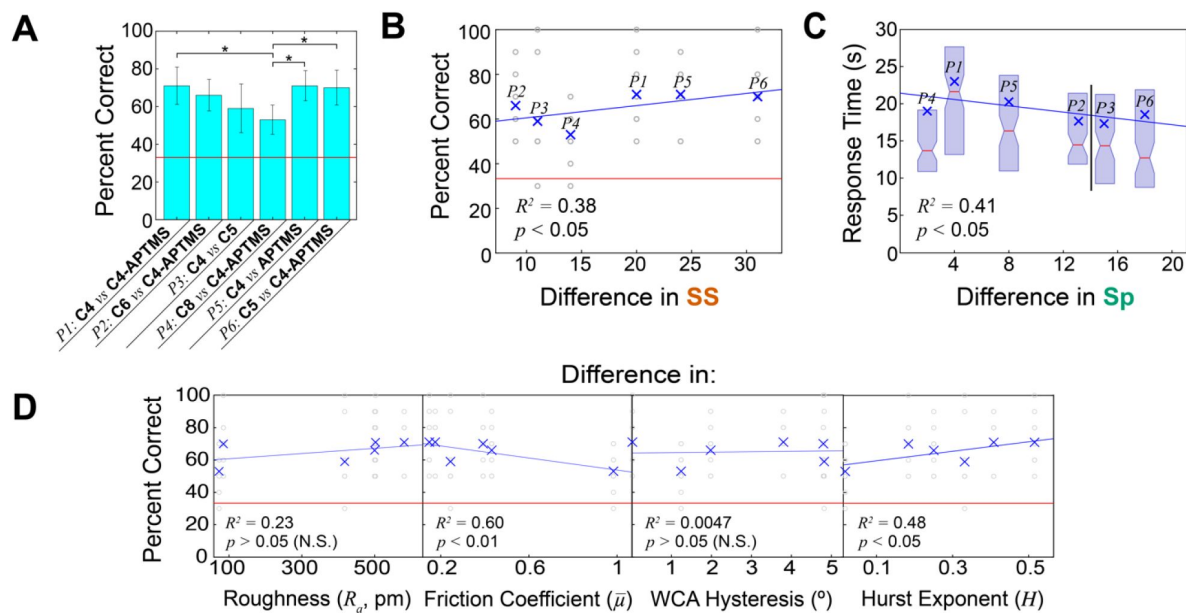


Fig. 2.

Human subjects testing for discriminability between surfaces. A) Average accuracies of all pairs in a 3-AFC task. All pairs were statistically significantly distinguishable above chance (red line, 33%). Error bars are represented as 95% confidence intervals around the means. Ends of brackets with (*) above denote statistically significantly different accuracy rates. B) Generalized linear mixed model (GLMM) of accuracy vs. the differences in steady sliding events. Accuracies of each trial across all subjects represented by gray $\circ$ marks, and global averages represented by blue $\times$ marks. C) GLMM of response times vs. the differences in stiction spike events. P2 and P3 have the same x-axis value and are shifted for clarity. Mean times are represented by blue ($\times$) marks, while medians are represented by red lines at notches of box plots. (D) GLMMs of accuracy vs. typically used material properties or parameters: average roughness R_a , global average friction coefficient across all conditions ($\bar{\mu}$), Hurst exponent H , and water contact angle hysteresis ($^\circ$) ($N = 10$ participants, $n = 600$ total trials).

Average response times for each pair were also fit to a GLMM to determine if the type of instability affected decision-making speeds. Participants were quicker to discriminate between surfaces as differences in stiction spike production increased ($p < 0.05$, shown in **Fig. 2C**), while there was no significant relationship between steady sliding or slow frictional waves on response times. This may be because stiction spikes are the most prevalent instability in all surfaces except **C6**, so occurrences of steady sliding or slow frictional waves against a background of stiction spikes may be important in forming tactile judgements. Supporting the idea that deviances from stiction spike occurrence were important, we found that they were not a predictor of subject accuracy, only response time.

To compare the value of looking at frictional instabilities, we also performed GLMM fits on common approaches in the field, like a friction coefficient or material property typically used in tactile discrimination, shown in **Fig. 2D**. Differences in average roughness R_a (or other parameters, like root mean square roughness R_{rms} (Fig. S5A of SI) did not show a statistically significant correlation to accuracy. Though roughness is a popular parameter, correlating any roughness parameter to human performance here could be moot: the limit of detecting roughness differences has previously been defined as 13 nm on structured surfaces²² and much higher for randomly rough surfaces,³⁸ all of which are magnitudes larger than the roughness differences between our surfaces.

For roughness and average coefficient of friction (typically and often problematically simplified as $F = \mu N$ across all tested conditions), one heuristic view is that any trends would correlate as friction is often thought to increase with roughness.³⁹ Instead, we observed a spurious, negative correlation between friction coefficient and accuracy; that is, the more different the surfaces are by friction coefficient, the less people can tell them apart. This spurious correlation would be the opposite of intuition, and further calls into question the common practice of using friction coefficients in touch-related studies. The alternative, two-term model which includes adhesive contact area for friction coefficient²⁴ was even less predictive (see Fig. S5A of SI). The differences in contact angle hysteresis – as an approximation of the adhesion contributions⁴⁰ – do not present any statistically significant effects on performance.

Interestingly, a large and statistically significant correlation is observed with the Hurst exponent H ($p < 0.05$), indicating differences in monolayer ordering are also likely to create distinct tactile feedback. This was expected since our silane-derived coatings cause frictional differences due to monolayer ordering.^{41,42} However, the Hurst exponent was positively correlated with response time (see Fig. S5B of SI), indicating that bigger differences in Hurst led to slower decision times which is counterintuitive. Thus, while Hurst exponent seems to work for accuracy in the surfaces here, it may not be generalizable to other types of surfaces.

Confirming Instability Formation During Human Exploration

To confirm that humans indeed form similar instabilities as the mock finger during exploration, we measured the tangential and normal force during a two-alternative forced choice (2-AFC) task. The participant placed their hands on a sensor stage, with one sample of **APTMS** under one hand and one sample of **C4** under the other. (**Fig. 3A**) The participant was then asked to explore each sample simultaneously, and ran over each surface in vertical, downward strokes until the participant could decide which of the two had “more friction”. **Fig. 3B-C** shows forces generated during exploration. As expected, the participant had higher variability in their force trace than a mock finger. Yet despite this variability, we see that friction instabilities identified in the mock finger are also present in the human finger. We observe characteristic formation of steady sliding, slow frictional waves, and stiction spikes. Slow frictional waves are notable because people are unlikely to intentionally oscillate their finger in such a rapid (~5 Hz) and consistent manner, especially since they were given no instruction to intentionally form the oscillations and generally slid their finger in a single motion.

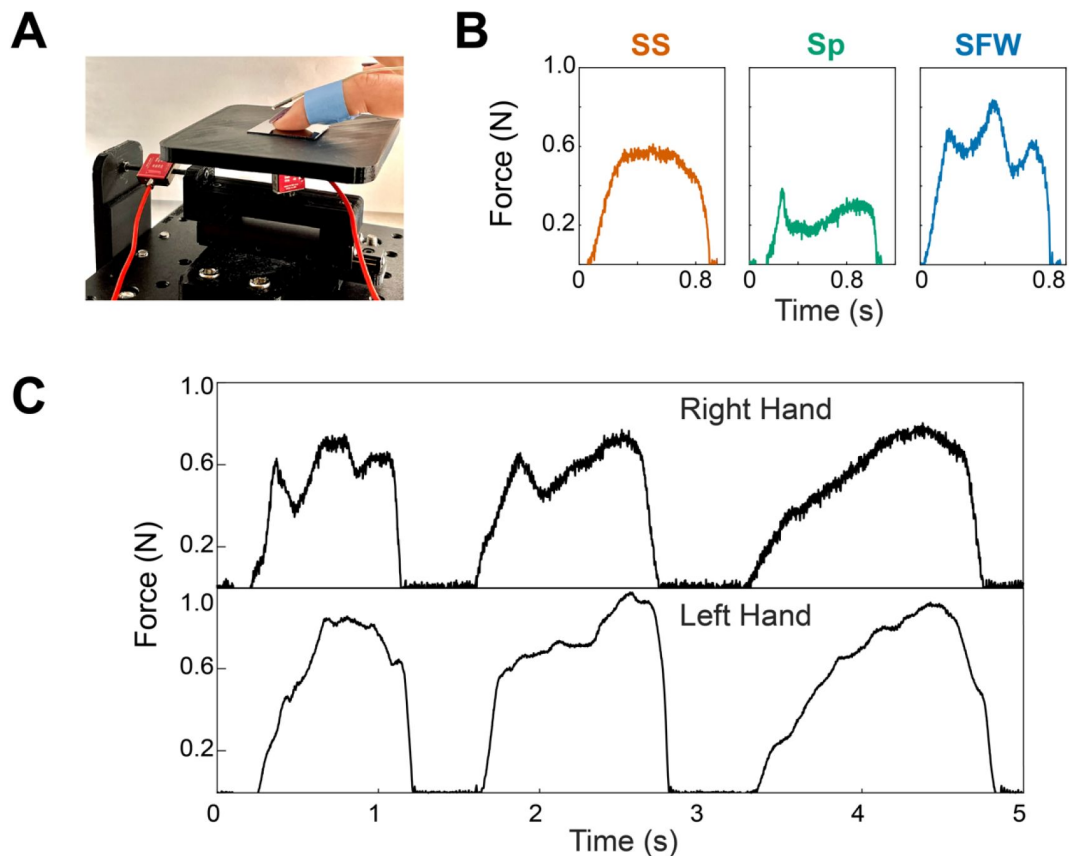


Fig. 3.

Recording friction of a human finger exploring a surface. A) Setup to measure tangential and normal forces during fine touch. A coated sample is securely double-sided taped to a stage, connected to two red sensors to record tangential and normal forces. A motion tracker is also placed on the moving finger to record displacement while sliding. Two setups are used simultaneously, one for each hand. B) Formation of all instability phases during human exploration. C) Tangential forces experienced by two hands on the same surface chemistry.

Conclusions

Here participants freely explored tactile minimal surfaces, which would not be expected to feel different to people based on nearly any common metric used in tactile perception. We further removed any confounding factors by asking participants to perform a low-level discrimination task, i.e., “which one does not feel like the others?”, instead of a subjective percept, like “which one feels rougher?”. We found that frictional instabilities explained how people are able to distinguish between the pairs found here. In these instabilities, we saw that stiction spikes drove how quickly participants decided between two surfaces. However, it was steady sliding that led to positive identification between surfaces, and slow frictional waves were negatively correlated and led to lower accuracy. This could be because slow frictional waves seemed to generally occur in the same exploration conditions. Thus, to create two surfaces that rapidly feel different, one limit could be a surface that only produces steady sliding versus stiction spikes. An example of this might be an oil-lubricated surface (steady sliding) versus a high-adhesion surface, like a freshly plasma-treated wafer.⁴³[44](#)

Instabilities are generated in a human finger, and the transitions between phases in different surfaces bridge the gap between the length scales relevant to molecular and mechanical phenomena. Instabilities may also help explain some aspects of tactile constancy, or the ability to retain object recognition properties despite varying environmental or human factors,⁴⁵[46](#) because instabilities themselves can be mathematically invariant to mass or velocity under certain conditions. In contrast, the raw friction force for a given experiment will vary with almost any input,⁴⁶[47](#) especially in macroscopic friction testing. Although the data gathered here came from a comparatively simple, single force sensor, we were still able to identify a trend that held across multiple substrates, which has been a longstanding challenge in the field. More sophisticated techniques, like spatially resolved force maps from digital image correlation⁴⁷[48](#) could benefit from categorizing instabilities features.

At this stage, it is not possible, *a priori*, to predict instabilities to a high degree of accuracy on real, experimental systems. Thus, characterizing surfaces by frictional instabilities will require mechanical testing. However, for those designing tactile interfaces in haptics or consumer goods, or extracting feature in tactile arrays and soft robotics, analyzing existing force data along instabilities may be more predictive than traditional material properties and more consistent than raw friction traces.

Acknowledgements

We acknowledge support from the National Eye Institute of the NIH (R01EY032584-03). XPS was conducted at the Surface Analysis Facility at the University of Delaware (NSF CHE-1428149). Atomic force microscopy was conducted at the Delaware Biotechnology Institute’s Bio-Imaging Center at the University of Delaware supported by grants from the NIH-NIGMS (P20 GM103446), the NSF (IIA-1301765), and the State of Delaware. J.G.A.C. is supported by NSF CAREER award 2234748. This study was conducted and approved by the Institutional Review Board of the University of Delaware (Project #1484385-7), with data from 10 healthy participants between the ages of 21 and 32.

References

- 1 Smith A. M., Scott S. H. 1996) **J. Neurophysiol** **75**:1957–1962
- 2 Khamis H., Afzal H. M. N., Sanchez J., Vickery R., Wiertlewski M., Redmond S. J., Birznieks I. 2021) **J. Neurophysiol** **125**:809–823
- 3 Ben-David O., Fineberg J. 2011) **Phys. Rev. Lett** **106**:254301
- 4 Skedung L., Harris K. L., Collier E. S., Rutland M. W. 2020) **Exp. Brain Res** **238**:1511–1524
- 5 Zhou X., Mo J. L., Li Y. Y., Xiang Z. Y., Yang D., Masen M. A., Jin Z. M. 2020) **Tribol. Lett** **68**:85
- 6 Rand C. J., Crosby A. J. 2006) **Appl. Phys. Lett** **89**:261907
- 7 Nolin A., Licht A., Pierson K., Lo C.-Y., Kayser L. V., Dhong C. 2021) **Soft Matter** **17**:5050–5060
- 8 Nolin A., Pierson K., Hlibok R., Lo C.-Y., Kayser L. V., Dhong C. 2022) **Soft Matter** **18**:3928–3940
- 9 Peng Y., Serfass C. M., Kawazoe A., Shao Y., Gutierrez K., Hill C. N., Santos V. J., Visell Y., Hsiao L. C. 2021) **Nat. Mater** **20**:1707–1711
- 10 Putelat T., Dawes J. H. P., Champneys A. R. 2017) **Proc. R. Soc. Math. Phys. Eng. Sci** **473**:20160606
- 11 Rice J. R., Ruina A. L. 1983) **J. Appl. Mech** **50**:343–349
- 12 Shoaib T., Heintz J., Lopez-Berganza J. A., Muro-Barrios R., Egner S. A., Espinosa-Marzal R. M. 2018) **Langmuir** **34**:756–765
- 13 Ruina A. 1983) **J. Geophys. Res. Solid Earth** **88**:10359–10370
- 14 Petrova D., Sharma D. K., Vacha M., Bonn D., Brouwer A. M., Weber B. 2020) **ACS Appl. Mater. Interfaces** **12**:9890–9895
- 15 Sahli R., Pallares G., Ducottet C., Ben Ali I. E., Al Akhrass S., Guibert M., Scheibert J. 2018) **Proc. Natl. Acad. Sci** **115**:471–476
- 16 Viswanathan K., Sundaram N. K., Chandrasekar S. 2016) **Soft Matter** **12**:5265–5275
- 17 Ndengue J., Dacleu, Cesini I., Faucheu J., Chatelet E., Zahouani H., Delafosse D., Massi F. 2017) **IEEE Trans. Haptics** **10**:409–417
- 18 Willemet L., Kanzari K., Monnoyer J., Birznieks I., Wiertlewski M. 2021) **Proc. Natl. Acad. Sci** **118**:e2109109118
- 19 Schwarz C. 2016) **Trends Neurosci** **39**:449–462
- 20 Gueorguiev D., Bochereau S., Mouraux A., Hayward V., Thonnard J.-L. 2016) **Sci. Rep** **6**:25553

- 21 Swain Z., Derkaloustian M., Hepler K. A., Nolin A., Damani V. S., Bhattacharyya P., Shrestha T., Medina J., Kayser L., Dhong C. 2024) **J. Mater. Chem. B** <https://doi.org/10.1039/D4TB01646G>
- 22 Skedung L., Arvidsson M., Chung J. Y., Stafford C. M., Berglund B., Rutland M. W. 2013) **Sci. Rep** **3**:2617
- 23 Dhong C., Kayser L. V., Arroyo R., Shin A., Finn M., Kleinschmidt A. T., Lipomi D. J. 2018) **Soft Matter** **14**:7483–7491
- 24 Israelachvili J. N. 2011) **Intermolecular and Surface Forces** Academic Press
- 25 Gao J., Luedtke W. D., Gourdon D., Ruths M., Israelachvili J. N., Landman U. 2004) **J. Phys. Chem. B** **108**:3410–3425
- 26 AliAbbasi E., Aydingul V., Sezgin A., Er U., Turkuz S., Basdogan C. 2023) **IEEE Trans. Haptics** **16**:586–593
- 27 Wasserman S. R., Tao Y. T., Whitesides G. M. 1989) **Langmuir** **5**:1074–1087
- 28 Zhu M., Lerum M. Z., Chen W. 2012) **Langmuir** **28**:416–423
- 29 Das S., Cadirov N., Chary S., Kaufman Y., Hogan J., Turner K. L., Israelachvili J. N. 2015) **J. R. Soc. Interface** **12**:20141346
- 30 Briggs G. A. D., Briscoe B. J. 1978) **Philos. Mag. A** **38**:387–399
- 31 Baumberger T., Caroli C., Ronsin O. 2002) **Phys. Rev. Lett** **88**:075509
- 32 Rand C. J., Crosby A. J. 2009) **J. Appl. Phys** **106**:064913
- 33 Viswanathan K., Sundaram N. K., Chandrasekar S. 2016) **Soft Matter** **12**:9185–9201
- 34 Persson B. N. J., Albohr O., Creton C., Peveri V. 2004) **J. Chem. Phys** **120**:8779–8793
- 35 Maksuta D., Dalvi S., Gujrati A., Pastewka L., Jacobs T. D. B., Dhinojwala A. 2022) **Soft Matter** **18**:5843–5849
- 36 Kingdom F. A. A., Prins N. 2016) **Psychophysics: A Practical Introduction** Academic Press
- 37 Xiao X.-D., Liu G., Charych D. H., Salmeron M. 1995) **Langmuir** **11**:1600–1604
- 38 Sahli R., Prot A., Wang A., Müser M. H., Piovarči M., Didyk P., Bennewitz R. 2020) **Sci. Rep** **10**:15800
- 39 Kietzig A.-M., Hatzikiriakos S. G., Englezos P. 2009) **J. Appl. Phys** **106**:024303
- 40 Chen Y. L., Helm C. A., Israelachvili J. N. 1991) **J. Phys. Chem** **95**:10736–10747
- 41 Lio A., Charych D. H., Salmeron M. 1997) **J. Phys. Chem. B** **101**:3800–3805
- 42 Xiao X., Hu J., Charych D. H., Salmeron M. 1996) **Langmuir** **12**:235–237
- 43 Drummond C., Israelachvili J. 2001) **Phys. Rev. E** **63**:041506

- 44 Donose B. C., Taran E., Vakarelski I. U., Shinto H., Higashitani K. 2006) **J. Colloid Interface Sci** **299**:233–237
- 45 Yoshioka T., Craig J. C., Beck G. C., Hsiao S. S. 2011) **J. Neurosci** **31**:17603–17611
- 46 Adams M. J., Johnson S. A., Lefèvre P., Lévesque V., Hayward V., André T., Thonnard J.-L. 2013) **J. R. Soc. Interface** **10**:20120467
- 47 Waters I., Alazmani A., Culmer P. 2020) **IEEE Trans. Med. Robot. Bionics** **2**:541–544

Author information

Maryanne Derkaloustian

Department of Materials Science and Engineering, University of Delaware, Newark, United States

Pushpita Bhattacharyya

Department of Psychological and Brain Sciences, University of Delaware, Newark, United States

Truc Ngo

Department of Biomedical Engineering, University of Delaware, Newark, United States

Joshua GA Cashaback

Department of Biomedical Engineering, University of Delaware, Newark, United States
ORCID iD: [0000-0002-8642-6648](https://orcid.org/0000-0002-8642-6648)

Jared Medina

Department of Psychological and Brain Sciences, University of Delaware, Newark, United States, Department of Psychology, Emory University, Atlanta, United States

Charles B Dhong

Department of Materials Science and Engineering, University of Delaware, Newark, United States, Department of Biomedical Engineering, University of Delaware, Newark, United States
ORCID iD: [0000-0003-3568-9859](https://orcid.org/0000-0003-3568-9859)

For correspondence: cdhong@udel.edu

Editors

Reviewing Editor

Yon Visell

Senior Editor

Tamar Makin

University of Cambridge, Cambridge, United Kingdom

Reviewer #1 (Public review):

Summary:

In this paper, Derkaloustian et. al look at the important topic of what affects fine touch perception. The observations that there may be some level of correlation with instabilities are intriguing. They attempted to characterize different materials by counting the frequency (occurrence #, not of vibration) of instabilities at various speeds and forces of a PDMS slab pulled lengthwise over the material. They then had humans make the same vertical motion to discriminate between these samples. They correlated the % correct in discrimination with differences in frequency of steady sliding over the design space as well as other traditional parameters such as friction coefficient and roughness. The authors pose an interesting hypothesis and make an interesting observation about the occurrences of instability regimes in different materials while in contact with PDMS, which is interesting for the community to see in the publication. It should be noted that the finger is complex, however, and there are many factors that may be quite oversimplified with the use of the PDMS finger, and the consideration and discounting of other parameters are not fully discussed in the main text or SI. Most importantly, however, the conclusions as stated do not align with the primary summary of the data in Figure 2.

Strengths:

The strength of this paper is in its intriguing hypothesis and important observation that instabilities may contribute to what humans are detecting as differences in these apparently similar samples.

Weaknesses:

The most important weakness is that the findings do not support the statements of findings made in the abstract. Of specific note in this regard is the primary correlation in Figure 2B between SS (steady sliding) and percent correct discrimination. While the statistical test shows significance (and is interesting!), the R-squared value is 0.38, while the R-squared value for the "Friction Coefficient vs. Percent Correct" plot has an R-squared of 0.6 and a p-value of < 0.01 (including Figure 2B). This suggests that the results do not support the claim in the abstract: "We found that participant accuracy in tactile discrimination was most strongly correlated with formations of steady sliding, and response times were negatively correlated with stiction spikes. Conversely, traditional metrics like surface roughness or average friction coefficient did not predict tactile discriminability." This is the most fundamental weakness of this paper.

Along the same lines, other parameters that were considered such as the "Percent Correct vs. Difference in Sp" and "Percent Correct vs. Difference in SFW" were not plotted for consideration in the SI. It would be helpful to compare these results with the other three metrics in order to fully understand the relationships. Other parameters such as stiction magnitude and differences in friction coefficient over the test space could also be important and interesting.

Beyond this fundamental concern, there is a weakness in the representativeness of the PDMS finger, the vertical motion, and the speed of sliding to real human exploration. The real finger has multiple layers with different moduli. In fact, the stratum corneum cells, which are the outer layer at the interface and determine the friction, have a much higher modulus than PDMS. In addition, the slanted position of the finger can cause non-uniform pressures across the finger. Both can contribute to making the PDMS finger have much more stick-slip than a real finger. In fact, if you look at the regime maps, there is very little space that has steady sliding. This does not represent well human exploration of surfaces. We do not tend to use a force and velocity that will cause extensive stick-slip (frequent regions of 100% stick-slip) and, in fact, the speeds used in the study are on the slow side, which also contributes to more stick-slip. At higher speeds and lower forces, all of the materials had steady sliding regions. Further, on these very smooth surfaces, the friction and stiction are more complex and

cannot dismiss considerations such as finger material property change with sweat pore occlusion and sweat capillary forces. Also, the vertical motion of both the PDMS finger and the instructed human subjects is not the motion that humans typically use to discriminate between surfaces. Finally, fingerprints may not affect the shape and size of the contact area, but they certainly do affect the dynamic response and detection of vibrations.

This all leads to the critical question, why are friction, normal force, and velocity not measured during the measured human exploration and in a systematic study using the real human finger? The authors posed an extremely interesting hypothesis that humans may alter their speed to feel the instability transition regions. This is something that could be measured with a real finger but is not likely to be correlated accurately enough to match regime boundaries with such a simplified artificial finger.

<https://doi.org/10.7554/eLife.104543.1.sa3>

Reviewer #2 (Public review):

Summary:

In this paper, the authors want to test the hypothesis that frictional instabilities rather than friction are the main drivers for discriminating flat surfaces of different sub-nanometric roughness profiles.

They first produced flat surfaces with 6 different coatings giving them unique and various properties in terms of roughness (picometer scale), contact angles (from hydrophilic to hydrophobic), friction coefficient (as measured against a mock finger), and Hurst exponent.

Then, they used those surfaces in two different experiments. In the first experiment, they used a mock finger (PDMS of 100kPa molded into a fingertip shape) and slid it over the surfaces at different normal forces and speeds. They categorized the sliding behavior as steady sliding, sticking spikes, and slow frictional waves by visual inspection, and show that the surfaces have different behaviors depending on normal force and speed. In a second experiment, participants (10) were asked to discriminate pairs of those surfaces. It is found that each of those pairs could be reliably discriminated by most participants.

Finally, the participant's discrimination performance is correlated with differences in the physical attributes observed against the mock finger. The authors found a positive correlation between participants' performances and differences in the count of steady sliding against the mock finger and a negative correlation between participants' reaction time and differences in the count of stiction spikes against the mock finger. They interpret those correlations as evidence that participants use those differences to discriminate the surfaces.

Strengths:

The created surfaces are very interesting as they are flat at the nanometer scale, yet have different physical attributes and can be reliably discriminated.

Weaknesses:

In my opinion, the data presented in the paper do not support the conclusions. The conclusions are based on a correlation between results obtained on the mock finger and results obtained with human participants but there is no evidence that the human participants' fingertips will behave similarly to the mock finger during the experiment. Figure 3 gives a hint that the 3 sliding behaviors can be observed in a real finger, but does not prove that the human finger will behave as the mock finger, i.e., there is no evidence that the

phase maps in Figure 1C are similar for human fingers and across different people that can have very different stiffness and moisture levels.

I believe that the authors collected the contact forces during the psychophysics experiments, so this shortcoming could be solved if the authors use the actual data, and show that the participant responses can be better predicted by the occurrence of frictional instabilities than by the usual metrics on a trial by trial basis, or at least on a subject by subject basis. I.e. Poor performers should show fewer signs of differences in the sliding behaviors than good performers.

The sample size (10) is very small.

<https://doi.org/10.7554/eLife.104543.1.sa2>

Reviewer #3 (Public review):

Strengths:

The paper describes a new perspective on friction perception, with the hypothesis that humans are sensitive to the instabilities of the surface rather than the coefficient of friction. The paper is very well written and with a comprehensive literature survey.

One of the central tools used by the author to characterize the frictional behavior is the frictional instabilities maps. With these maps, it becomes clear that two different surfaces can have both similar and different behavior depending on the normal force and the speed of exploration. It puts forward that friction is a complicated phenomenon, especially for soft materials.

The psychophysics study is centered around an odd-one-out protocol, which has the advantage of avoiding any external reference to what would mean friction or texture for example. The comparisons are made only based on the texture being similar or not.

The results show a significant relationship between the distance between frictional maps and the success rate in discriminating two kinds of surface.

Weaknesses:

The main weakness of the paper comes from the fact that the frictional maps and the extensive psychophysics study are not made at the same time, nor with the same finger. The frictional maps are produced with an artificial finger made out of PDMS which is a poor substitute for the complex tribological properties of skin.

The evidence would have been much stronger if the measurement of the interaction was done during the psychophysical experiment. In addition, because of the protocol, the correlation is based on aggregates rather than on individual interactions.

The authors compensate with a third experiment where they used a 2AFC protocol and an online force measurement. But the results of this third study, fail to convince the relation.

No map of the real finger interaction is shown, bringing doubt to the validity of the frictional map for something as variable as human fingers.

<https://doi.org/10.7554/eLife.104543.1.sa1>

Author response:

eLife Assessment

This useful study integrates experimental methods from materials science with psychophysical methods to investigate how frictional instabilities influence tactile surface discrimination. The authors argue that force fluctuations arising from transitions between frictional sliding conditions facilitate the discrimination of surfaces with similar friction coefficients. However, the reliance on friction data obtained from an artificial finger, together with the ambiguous correlative analyses relating these measurements to human psychophysics, renders the findings incomplete.

Our main goal with this paper was to show that the most common metric, i.e. average friction coefficient—widely used in tactile perception and device design—is fundamentally unsound, and to offer a secondary parameter that is compatible with the fact that human motion is unconstrained, leading to dynamic interfacial mechanics. In contrast with the summary assessment, we also note that the average friction coefficients in our study were not particularly similar, ranging from differences of 0.4 – 1, a typical range seen in most studies. We believe some of the comments originate from a misinterpretation of our statistically significant, but negative correlation between human results and friction coefficients – which leads to the spurious conclusion that nearly identical objects should be very easy to tell apart, thus supporting our central argument for the need of an alternative. We understand the Reviewers wanting to see that we can demonstrate that humans using instabilities *in situ*. This is seemingly reasonable, but we explain the significant challenges and fundamental unknowns to those experiments. However, we modified our title to reflect our focus on offering an alternative to the average coefficient of friction.

We do not think it was feasible, at this stage, to demonstrate that humans use friction instabilities through direct manipulation and observation in human participants. In short, there are still several fundamental unknowns: (1) a decision-making model would need to be created, but it is unknown if tactile decision making follows other models, (2) it is further unknown what constitutes “tactile evidence”, though at our manuscript’s conclusion, we propose that friction instabilities are better suited for to be tactile evidence than the averaging of friction coefficients from a narrow range of human exploration (3) in the design of samples, from a friction mechanics and materials perspective, it is not at this point, possible to pre-program surfaces *a priori* to deliver friction instabilities and instead must be experimentally determined – especially when attempting to achieve this in controlled surfaces that do not create other overriding tactile cues, like macroscopic bumps or large differences in surface roughness. (4) Given that the basis for tactile percepts, like which object feels “rougher” or “smoother” is not sufficiently established and we have seen leads to confusion, it is necessary to use a 3-alternative forced choice task which avoids asking objects along a preset perceptual dimension – a challenge recognized by Reviewer 3. However, this would bring in issues of memory in the decision-making model. (5) The prior points are compounded by the fact that, we believe, tactile exploration must be performed in an unconstrained manner, i.e., without an apparatus generating motion onto a stationary finger. Work by Liu et al. (IEEE ToH, 2024) showed that recreating friction obtained during free exploration onto a stationary finger was uninterpretable by the participants, hinting at the importance of efference copies(1). We believe that each of the above-mentioned issues constitutes a significant advance in knowledge and would require discussion and dissemination with the community. Finally, one of our overarching goals is to create a consistent method to characterize surfaces, and given individual variability in human fingers and motion, a machine-based method that can rapidly, consistently, and sufficiently replicate tactile exploration is needed.

Finally, we also justify our use of a mock finger to provide a method to characterize surfaces in tactile studies that other researchers could reasonably recreate, without creating a

standard around individual humans, considering the variability in finger shape and motion during exploration. We do not believe this is an “either-or” argument, but rather that standardized methods to characterize surfaces and devices are greatly needed in the field. From these standardized methods, like surface roughness, some tabulated values of friction coefficient, or surface energy, etc., the current metrics to parameterize results are largely incapable of capturing the dynamic changes in forces expected during human tactile exploration.

Our changes to the manuscript (Page 1 & SI Page 1, Title)

“Alternatives to Friction Coefficient: Role of Frictional Instabilities for Fine Touch Perception”

Reviewer 1 (Public review):

Summary:

In this paper, Derkaloustian et. al look at the important topic of what affects fine touch perception. The observations that there may be some level of correlation with instabilities are intriguing. They attempted to characterize different materials by counting the frequency (occurrence #, not of vibration) of instabilities at various speeds and forces of a PDMS slab pulled lengthwise over the material. They then had humans make the same vertical motion to discriminate between these samples. They correlated the % correct in discrimination with differences in frequency of steady sliding over the design space as well as other traditional parameters such as friction coefficient and roughness. The authors pose an interesting hypothesis and make an interesting observation about the occurrences of instability regimes in different materials while in contact with PDMS, which is interesting for the community to see in the publication. It should be noted that the finger is complex, however, and there are many factors that may be quite oversimplified with the use of the PDMS finger, and the consideration and discounting of other parameters are not fully discussed in the main text or SI. Most importantly, however, the conclusions as stated do not align with the primary summary of the data in Figure 2.

Strengths:

The strength of this paper is in its intriguing hypothesis and important observation that instabilities may contribute to what humans are detecting as differences in these apparently similar samples.

We thank Reviewer 1 for their time on the manuscript, recognizing the approach we took, and offering constructive feedback. We believe that our conclusions, in fact, are supported by the primary summary of the data in Figure 2 but we believe that our use of R^2 could have led to misinterpretation. The trend with friction coefficient and percent correct was indeed statistically significant but was spurious because the slope was negative. In the revision, we add clarifying comments throughout, change from R^2 to r as to highlight the negative trend, and adjust the figures to better focus on friction coefficient.

Finally, we added a new section to discuss the tradeoffs between using a real human finger versus a mock finger, and which situations may warrant the use of one or the other. In short, for our goal of characterizing surfaces to be used in tactile experiments, we believe a mock finger is more sustainable and practical than using real humans because human fingers are unique per participant, humans move their fingers at constantly changing pressures and velocities, and friction generated during free exploring human cannot be satisfactorily replicated by moving a sample onto a stationary finger. But, we do not disagree that for other types of experiments, characterizing a human participant directly may be more advantageous.

Weaknesses:

Comment 1 - The most important weakness is that the findings do not support the statements of findings made in the abstract. Of specific note in this regard is the primary correlation in Figure 2B between SS (steady sliding) and percent correct discrimination. Of specific note in this regard is the primary correlation in Figure 2B between SS (steady sliding) and percent correct discrimination. While the statistical test shows significance (and is interesting!), the R-squared value is 0.38, while the R-squared value for the "Friction Coefficient vs. Percent Correct" plot has an R-squared of 0.6 and a p-value of < 0.01 (including Figure 2B). This suggests that the results do not support the claim in the abstract: "We found that participant accuracy in tactile discrimination was most strongly correlated with formations of steady sliding, and response times were negatively correlated with stiction spikes. Conversely, traditional metrics like surface roughness or average friction coefficient did not predict tactile discriminability."

We disagree that the trend with friction coefficient suggests the results do not support the claim because the correlation was found to be negative. However, we could have made the comparison more apparent and expanded on this point, given its novelty.

While the R^2 value corresponding to the "Friction Coefficient vs. Percent Correct" plot is notably higher, our results show that the slope is negative, which would be statistically spurious. This is because a negative correlation between percent correct (accuracy in discriminating surfaces) and difference in friction coefficient means that the more similar two surfaces are (by friction coefficient), the easier it would be for people to tell them apart. That is, it incorrectly concludes that two identical surfaces would be much easier to tell apart than two surfaces with greatly different friction coefficients.

This is counterintuitive to nearly all existing results, but we believe our samples were well-positioned to uncover this trend by minimizing variability, by controlling multiple physical parameters in the samples, and that the friction coefficient — typically calculated in the field as an average friction coefficient — ignores all the dynamic changes in forces present in elastic systems undergoing mesoscale friction, i.e., human touch, as seen in Fig. 1 in a mock finger and Fig. 3 in a real finger. By demonstrating this statistically spurious trend, we believe this strongly supports our premise that an alternative to friction coefficient is needed in the design of tactile psychophysics and haptic interfaces.

We believe that this could have been misinterpreted, so we took several steps to improve clarity, given the importance of this finding: we separated the panel on friction coefficient to its own panel, we changed from R^2 to r throughout, and we added clarifying text. We also added a small section focusing on this spurious trend.

Our changes to the manuscript (Page 10)

"To compare the value of looking at frictional instabilities, we also performed GLMM fits on common approaches in the field, like a friction coefficient or material property typically used in tactile discrimination, shown in Fig. 2D-E. Interestingly, in Fig. 2D, we observed a spurious, negative correlation between friction coefficient (typically and often problematically

simplified as $F = \mu N$ across all tested conditions) and accuracy ($r = -0.64$, $p < 0.01$); that is, the

more different the surfaces are by friction coefficient, the less people can tell them apart. This spurious correlation would be the opposite of intuition, and further calls into question the common practice of using friction coefficients in touch-related studies. The alternative, two-term model which includes adhesive contact area for friction coefficient (29) was even less predictive (see Fig. S6A of SI). We believe such a correlation could not have been uncovered

previously as our samples are minimal in their physical variations. Yet, the dynamic changes in force even within a single sample are not considered, despite being a key feature of mesoscale friction during human touch.

We investigate different material properties in Fig. 2E. Differences in average roughness R_a (or other parameters, like root mean square roughness R_{rms} (Fig. S6A of SI) did not show a statistically significant correlation to accuracy. Though roughness is a popular parameter, correlating any roughness parameter to human performance here could be moot: the limit of detecting roughness differences has previously been defined as 13 nm on structured surfaces³³ and much higher for randomly rough surfaces,⁽⁴⁶⁾ all of which are magnitudes larger than the roughness differences between our surfaces. The differences in contact angle hysteresis – as an approximation of the adhesion contributions⁽⁴⁷⁾ – do not present any statistically significant effects on performance.”

Comment 2, Part 1

Along the same lines, other parameters that were considered such as the "Percent Correct vs. Difference in Sp" and "Percent Correct vs. Difference in SFW" were not plotted for consideration in the SI. It would be helpful to compare these results with the other three metrics in order to fully understand the relationships.

We have added these plots to the SI. We note that we had checked these relationships and discussed them briefly, but did not include the plot. The plots show that the type of instability was not as helpful as its presence or absence.

Our changes to the manuscript (Page 9)

“Furthermore, a model accounting for slow frictional waves alone specifically shows a significant, negative effect on performance ($p < 0.01$, Fig. S5 of SI), suggesting that in these samples and task, the type of instability was not as important.”

Added (SI Page 4)

“and no correlation between accuracy and stiction spikes (Fig. S5).”

Comment 2, Part 2

Other parameters such as stiction magnitude and differences in friction coefficient over the test space could also be important and interesting.

We agree these are interesting and have thought about them. We are aware that others, like Gueorguiev et al., have studied stiction magnitudes, and though there was a correlation, the physical differences in surface roughness (glass versus PMMA) investigated made it unclear if these could be generalized further⁽²⁾. We are unsure how to proceed here with a satisfactory analysis of stiction magnitude, given that stiction spikes are not always generated. In fact, Fig. 1 shows that for many velocities and pressures, they do not form. However, we offer some speculation on why stiction spikes may be overrepresented in the literature because:

- (1) They are prone to being created if the finger was loaded for a long time onto a surface prior to movement, thus creating adhesion by contact aging which is unlike active human exploration. We avoid this by discarding the first pull in our measurements, and is a standard practice in mechanical characterization if contact aging needs to be avoided.
- (2) The ranges of velocities and pressures explored were small.
- (3) In an effort to generate strong tactile stimuli, highly adhesive or rough surfaces are used.

(4) They are visually distinctive on a plot, but we are unaware of any mechanistic reason that mechanoreceptors would be extremely sensitive to this low frequency event over other signals.

In ongoing work, however, we are always cognizant that if stiction spikes are a dominant factor, then a secondary analysis on their magnitude would be important.

We interpret “difference in friction coefficient over the test space” to be, for a single surface, like C4, to find the highest average friction for a condition of single velocity and mass and subtract that from the lowest average friction for a condition of single velocity and mass. We calculated the difference in friction coefficient in the typical manner of the field, by averaging all data collected at all velocities and masses and assigning a single value for all of a surface, like C4. We had performed this, and have the data, but we are wary of overinterpreting secondary and tertiary metrics because they do not have any fundamental basis in traditional tribology, and this value, if used by humans, would suggest that they rapidly explore a large parameter space to find a “maximum” and “minimum” friction. Furthermore, the range in friction across the test space, after averaging, may in fact, be smaller than the range of friction in a single measurement. For example, in Fig. 1B, the friction coefficient can be calculated by dividing the data by the normal force ([applied mass + 6 g finger] × gravity). The friction coefficient in a single run varies widely, as expected.

Fig. 2D shows a GLMM fit between percent correct responses across our pairs and the differences in friction coefficient for each pair, where we see a spurious negative correlation. As we had the data of all average friction coefficients for each condition for a given material, we also looked at the difference in maximum and minimum friction coefficients. For our tested pairs, these differences also lined up on a statistically significant, negative GLMM fit ($r = -0.86$, $p < 0.005$). However, the values for a given surface can vary drastically, with an interquartile range of 1.20 to 2.09 on a single surface. We fit participant accuracy to the differences in these IQRs across pairs. This also led to a negative GLMM fit ($r = -0.65$, $p < 0.05$). However, we are hesitant to add this to the manuscript for the reasons stated previously.

Comment 3, Part 1

Beyond this fundamental concern, there is a weakness in the representativeness of the PDMS finger, the vertical motion, and the speed of sliding to real human exploration.

Overall, this is a continuous debate that we think offers two solutions. There is always a tradeoff between using a synthetic model of a finger versus a real human finger, and there is a place for both models. That is, while our mock finger will be more successful the closer it is to a human finger, it is not our goal to fully replace a human finger, rather our goal is to provide a method of characterizing surfaces that is indeed relevant on the length scale of human touch.

The usefulness of the mock finger is in isolating the features of each surface that is independent of human variability, i.e., instabilities that form without changing loading conditions between sliding motions or even within one sliding motion. Of course, with this method, we still require confirmation of these features still forming during human exploration, which we show in Fig. 3.

We believe that this method of characterizing surfaces at the mesoscale will ultimately lead to more successful human studies on tactile perception. Currently, and as shown in the paper, characterizing surfaces through traditional techniques, such as a commercial tribometer (friction coefficient, using a steel or hard metal ball), roughness (via atomic force microscopy or some other metrology), surface energy are less predictive. Thus, we believe this mock finger is stronger than the current state-of-the-art characterizing surfaces (we are also aware

of a commercial mock finger company, but we were unable to purchase or obtain an evaluation model).

One of the main – and severe – limitations of using a human finger is that all fingers are different, meaning any study focusing on a particular user may not apply to others or be recreated easily by other researchers. We cannot set a standard for replication around a real human finger as that participant may no longer be available, or willing to travel the world as a “standard”. Furthermore, the method in which changes their pressures and velocities is different. We note that this is a challenge unique to touch perception – how an object is touched changes the friction generated, and thus the tactile stimulus generated, whereas a standardized stimulus is more straightforward for light or sound.

However, we do emphasize that we have strongly considered the balance between feasibility and ecological validity in the design of a mock finger. We have a mock finger, with the three components of stiffness of a human finger (more below). Furthermore, we have also successfully used this mock finger in correlations with human psychophysics in previous work, where findings from our mechanical experiments were predictive of human performance(3-6).

Our changes to the manuscript Added (Page 2-3)

“Mock finger as a characterization tool

In this work, we use a mechanical setup with a PDMS mock finger to derive tactile predictors from controlled friction traces alternative to average friction coefficients. While there is a tradeoff in selecting a synthetic finger over a more accurate, real human finger in modeling touch, our aim to design a method of mesoscale surface characterization for more successful studies on tactile perception cannot be fulfilled using one human participant as a standard. We believe that with sufficient replication of surface and bulk properties as well as contact geometry, and controlled friction measurements collected at loading conditions observed during a tactile discrimination task, we can isolate unique frictional features of a set of surfaces that do not arise from human-to-human variability.

The major component of a human finger, by volume, is soft tissue (~56%)(22), resulting in an effective modulus close to 100 kPa(23,24). In order to achieve this same softness, we crosslink PDMS in a 1×1×5 cm mold at a 30:1 elastomer:crosslinker ratio. However, two more features impart increased stiffness in a human finger. Most of this added rigidity is derived from the bone at the fingertip, the distal phalanx(23–25), which we mimic with an acrylic bone within our PDMS network. The stratum corneum, the stiffer, glassier outer layer of skin(26), is replicated with the surface of the mock finger glassified, or further crosslinked, after 8 hours of UV-Ozone treatment(27). This treatment also modifies the surface properties of the native PDMS to align with those of a human finger more closely. It minimizes the viscoelastic tack at the surface, resulting in a comparable non-sticky surface. At least one day after treatment, the finger surface returns to moderate hydrophilicity (~60°), as is typically observed for a real finger(28).

The initial contact area formed before a friction trace is collected is a rectangle of 1×1 cm. While this shape is not entirely representative of a human finger with curves and ridges, human fingers flatten out enough to reduce the effects of curvature with even very light pressures(28–30). This implies that regardless of finger pressure, the contact area is largely load-independent, which is more accurately replicated with a rectangular mock finger. It is still a challenge to control pressure distribution with this planar interface, but non-uniform pressures are also expected during human exploration.

Lastly, we consider fingerprints vs. flat fingers. A key finding of our previous work is that while fingerprints enhanced frictional dynamics at certain conditions, key features were still maintained with a flat finger.⁷ Furthermore, for some loading conditions, the more amplified

signals could also result in more similar friction traces for different surfaces. We have continued to use flat fingers in our mechanical experiments, and have observed good agreement between these friction traces and human experiments(7,8,21,31).”

(Page 3-4, Materials and Methods)

“Mock Finger Preparation

Friction forces across all six surfaces were measured using a custom apparatus with a polydimethylsiloxane (PDMS, Dow Sylgard 184) mock finger that mimics a human finger’s

mechanical properties and contact mechanics while exploring a surface relatively closely(7,8). PDMS and crosslinker were combined in a 30:1 ratio to achieve a stiffness of 100 kPa comparable to a real finger, then degassed in a vacuum desiccator for 30 minutes. We are aware that the manufacturer recommended crosslinking ratio for Sylgard 184 is 10:1 due to potential uncrosslinked liquid residues(32), but further crosslinking concentrated at the surface prevents this. The prepared PDMS was then poured into a 1×1×5 cm mold also containing an acrylic 3D-printed “bone” to attach applied masses on top of the “fingertip” area contacting a surface during friction testing. After crosslinking in the mold at 60°C for 1 hour, the finger was treated with UV-Ozone for 8 hours out of the mold to minimize viscoelastic tack.

Mechanical Testing

A custom device using our PDMS mock finger was used to collect macroscopic friction force traces replicating human exploration(7,8). After placing a sample surface on a stage, the finger was lowered at a slight angle such that an initial 1×1 cm rectangle of “fingertip” contact area could be established. We considered a broad range of applied masses ($M = 0, 25, 75, \text{ and } 100 \text{ g}$) added onto the deadweight of the finger (6 g) observed during a tactile discrimination task. The other side of the sensor was connected to a motorized stage (V-508 PIMag Precision Linear Stage, Physikinstrumente) to control both displacement (4 mm across all conditions) and sliding velocity ($v = 5, 10, 25, \text{ and } 45 \text{ mm s}^{-1}$). Forces were measured at all 16 combinations of mass and velocity via a 250 g Futek force sensor ($k = 13.9 \text{ kN m}^{-1}$) threaded to the bone, and recorded at an average sampling rate of 550 Hz with a Keithley 7510 DMM digitized multimeter. Force traces were collected in sets of 4 slides, discarding the first due to contact aging. Because some mass-velocity combinations were near the boundaries of instability phase transitions, not all force traces at these given conditions exhibited similar profiles.

Thus, three sets were collected on fresh spots for each condition to observe enough occurrences of multiple instabilities, at a total of nine traces per combination for each surface.”

Added References (Page 13)

M. Murai, H.-K. Lau, B. P. Pereira and R. W. H. Pho, *J. Hand Surg.*, 1997, 22, 935–941.

A. Abdouni, M. Djaghoul, C. Thieulin, R. Vargiolu, C. Pailler-Mattei and H. Zahouani, *R. Soc. Open Sci.*, DOI:10.1098/rsos.170321.

P.-H. Cornuault, L. Carpentier, M.-A. Bueno, J.-M. Cote and G. Monteil, *J. R. Soc. Interface*, DOI:10.1098/rsif.2015.0495.

K. Qian, K. Traylor, S. W. Lee, B. Ellis, J. Weiss and D. Kamper, *J. Biomech.*, 2014, 47, 3094–3099.

Y. Yuan and R. Verma, *Colloids Surf. B Biointerfaces*, 2006, 48, 6–12.

Y.-J. Fu, H. Qui, K.-S. Liao, S. J. Lue, C.-C. Hu, K.-R. Lee and J.-Y. Lai, *Langmuir*, 2010, 26, 4392–4399.

Comment 3, Part 2

“The real finger has multiple layers with different moduli. In fact, the stratum corneum cells, which are the outer layer at the interface and determine the friction, have a much higher modulus than PDMS. The real finger has multiple layers with different moduli. In fact, the stratum corneum cells, which are the outer layer at the interface and determine the friction, have a much higher modulus than PDMS.

We have approximated the softness of the finger with 100 kPa crosslinked PDMS, which is close to what has been reported for the bulk of a human fingertip(8,9). However, as mentioned in the Materials and Methods, there are two additional features of the mock finger that impart greater strength. The PDMS surrounds a rigid, acrylic bone comparable to the distal phalanx, which provides an additional layer of higher modulus(10). Additionally, the 8-hour UV-Ozone treatment decreases the viscoelastic tack of the pristine PDMS by glassifying, or further crosslinking the surface of the finger(11), therefore imparting greater stiffness at the surface similar to the contributions of the stratum corneum, along with a similar surface energy(12). This technique is widely used in wearables(13), soft robotics(14), and microfluidics(15) to induce both these material changes. Additionally, the finger is used at least a day after UV-Ozone treatment is completed in order for the surface to return to moderate hydrophilicity, similar to the outermost layer of human skin(16).

Comment 3, Part 3

In addition, the slanted position of the finger can cause non-uniform pressures across the finger. Both can contribute to making the PDMS finger have much more stick-slip than a real finger.

To ensure that there is minimal contribution from the slanted position of the finger, an initial contact area of 1×1 cm is established before sliding and recording friction measurements. As the PDMS finger is a soft object, the portion in contact with a surface flattens and the contact area remains largely unchanged during sliding. Any additional stick-slip after this alignment step is caused by contact aging at the interface, but the first trace we collect is always discarded to only consider stick-slip events caused by surface chemistry. We recognize that it is difficult to completely control the pressure distribution due to the planar interface, but this is also expected when humans freely explore a surface.

Comment 3, Part 4

In fact, if you look at the regime maps, there is very little space that has steady sliding. This does not represent well human exploration of surfaces. We do not tend to use a force and velocity that will cause extensive stick-slip (frequent regions of 100% stick-slip) and, in fact, the speeds used in the study are on the slow side, which also contributes to more stick-slip. At higher speeds and lower forces, all of the materials had steady sliding regions.

We are not aware of published studies that extensively show that humans avoid stickslip regimes. In fact, we are aware familiar with literature where stiction spike formation is suppressed – a recent paper by AliAbbasi, Basdogan et. al. investigates electroadhesion and friction with NaCl solution-infused interfaces, resulting in significantly steadier forces(17). We also directly showed evidence of instability formation that we observed during human exploration in Fig. 3B-C. These dynamic events are common, despite the lack of control of

normal forces and sliding velocities. We also note that Reviewer 1, Comment 2, was suggesting that we further explore possible trends from parameterizing the stiction spike.

We note that many studies have often not gone at the velocities and masses required for stiction spikes – even though these masses and velocities would be routinely seen in free exploration – this is usually due to constraints of equipment(18). Sliding events during human free exploration of surfaces can exceed 100 mm/s for rapid touches. However, for the surfaces investigated here, we observe that large regions of stick-slip can emerge at velocities as low as 5 mm/s depending on the applied load. The incidence of steady sliding appears more dependent on the applied mass, with almost no steady sliding observed at or above 75 g. Indeed, the force categorization along our transition zones is the main point of the paper.

Comment 3, Part 5

Further, on these very smooth surfaces, the friction and stiction are more complex and cannot dismiss considerations such as finger material property change with sweat pore occlusion and sweat capillary forces. Also, the vertical motion of both the PDMS finger and the instructed human subjects is not the motion that humans typically use to discriminate between surfaces.

We did not describe the task sufficiently. Humans were only given the instruction to slide their finger along a single axis from top to bottom of a sample, not vertical as in azimuthal to gravity. We have updated our wording in the manuscript to reflect this.

Our changes to the manuscript (Page 4)

“Participants could touch for as long as they wanted, but were asked to only use their dominant index fingers along a single axis to better mimic the conditions for instability formation during mechanical testing with the mock finger.”

(Page 11)

“The participant was then asked to explore each sample simultaneously, and ran over each surface in strokes along a single axis until the participant could decide which of the two had “more friction”.”

Comment 3, Part 6

Finally, fingerprints may not affect the shape and size of the contact area, but they certainly do affect the dynamic response and detection of vibrations.

We are aware of the nuance. Our previous work on the role of fingerprints on friction experienced by a PDMS mock finger showed enhanced signals with the incorporation of ridges on the finger and used a rate-and-state model of a heterogenous, elastic body to find corresponding trends (though there is no existing model of friction that can accurately model experiments on mesoscale friction)(7). The key conclusion was that a flat finger still preserved key dynamic features, and the presence of stronger or more vibrations could result in more similar forces for different surfaces depending on the sliding conditions.

This is also in the context that we are seeking to provide a reasonable and experimentally accessible method to characterize surfaces, which will always be better as we get closer in replicating a true human finger. But our goal here was to replicate the finger sufficiently for use in human studies. We believe the more appropriate metric of success is if the mock finger is more successful than replacing traditional characterization experiments, like friction coefficient, roughness, surface energy, etc.

Comment 4

This all leads to the critical question, why are friction, normal force, and velocity not measured during the measured human exploration and in a systematic study using the real human finger? The authors posed an extremely interesting hypothesis that humans may alter their speed to feel the instability transition regions. This is something that could be measured with a real finger but is not likely to be correlated accurately enough to match regime boundaries with such a simplified artificial finger.

We are excited that our manuscript offers a tractable manner to test the hypothesis that tactile decision-making models use friction instabilities as evidence. However, we lay out the challenges and barriers, and how the scope of this paper will lead us in that direction. We also clarify that our goals are to provide a method to characterize samples to better design tactile interfaces in haptics or in psychophysical experiments and raise awareness that the common methods of sample characterization in touch by an average friction coefficient or roughness is fundamentally unsound.

In short, in our view, to further support our findings on instabilities would require answering:

- (1) Which one, or combination of, of the multiple swipes that people make responsible for a tactile decision? (The need for a decision-making model)
- (2) Establish what is, or may be, tactile evidence.
- (3) Establish tactile decision-making models are similar or different than existing decision-making models.
- (4) Test the hypothesis, in these models, that friction instabilities are evidence, and not some other unknown metric. This requires design samples that vary in the amount of evidence generated, but this evidence cannot be controlled directly. Rather, the samples indirectly vary evidence by how likely it is for a human to generate different types of friction instabilities during standard exploration.
- (5) Design a task that does not require the use of subjective tactile descriptors, like “which one feels rougher”, which we see cause confusion in participants, which will likely require accounting for memory effects.

We elaborate these points below:

To successfully perform this experiment, we note that freely exploring humans make multiple strokes on a surface. Therefore, we would need to construct a decision-making model. It has not yet been demonstrated whether tactile decision making follows visual decision making, but perhaps to start, we can assume it does. Then, in the design of our decision-making paradigm, we immediately run into the problem: What is tactile evidence?

From Fig. 3C, we already can see that identifying evidence is challenging. Prior to this manuscript, people may have chosen the average force, or the highest force. Or we may choose the average friction force. Then, after deciding on the evidence, we need to find a method to manipulate the evidence, i.e., create samples or a machine that causes high friction, etc. We show that during the course of human touch, due to the dynamic nature of friction, the average can change a large amount and sample design becomes a central barrier to experiments. Others may suggest immobilizing the finger and applying a known force, but given how much friction changes with human exploration, there is no known method to make a machine recreate temporally and spatially varying friction forces during sliding onto a stationary finger. Finally, perhaps most importantly, in addition to mechanical challenges, a study by Liu, Colgate et al. showed that even if they recorded the friction (2D) of a finger exploring a surface and then replicated the same friction forces onto a finger, the participant

could not determine which surface the replayed friction force was supposed to represent.¹ This supports that the efference copy is important, that the forces in response to expected motion are important to determine friction. Finally, there is no known method to design instabilities *a priori*. They must be found through experiments. Especially since if we were to introduce, say a bump or a trough, then we bring in confounding variables to how participants tell surfaces apart.

Furthermore, even if we had some consistent method to create tactile “evidence”, the paradigm also deserves some consideration. In our experience, the 3-AFC task we perform is important because the vocabulary for touch has not been established. That is, in 3-AFC, by asking to determine which one sample is unlike the others, we do not have to ask the participant questions like “which one is rougher” or “which one has less friction”. In contrast, 2-AFC, which is better for decision-making models because it does not include memory, requires the asking of a perceptual question like: “which one is rougher?”. In our ongoing work, taking two silane coatings, we found that participants could easily identify which surface is unlike the others above chance in a 3-AFC, but participants, even within their own trials, could not consistently identify one silane as perceptually “rougher” by 2-AFC. To us, this calls into question the validity of tactile descriptors, but is beyond the scope of this manuscript.

This is not our only goal, but in the context of human exploration, in this manuscript here, we believed it was important to identify a mechanical parameter that was consistent with how humans explore surfaces, but was also a parameter that could characterize to some consistent property of a surface – irrespective of whether a human was touching it. We thought that designing human decision-making models and paradigms around the friction coefficient would not be successful.

Given the scope of these challenges, we do not think it would be possible to establish these conceptual sequences in a single manuscript.

Reviewer 2 (Public review):

Summary:

In this paper, the authors want to test the hypothesis that frictional instabilities rather than friction are the main drivers for discriminating flat surfaces of different sub-nanometric roughness profiles.

They first produced flat surfaces with 6 different coatings giving them unique and various properties in terms of roughness (picometer scale), contact angles (from hydrophilic to hydrophobic), friction coefficient (as measured against a mock finger), and Hurst exponent.

Then, they used those surfaces in two different experiments. In the first experiment, they used a mock finger (PDMS of 100kPA molded into a fingertip shape) and slid it over the surfaces at different normal forces and speeds. They categorized the sliding behavior as steady sliding, sticking spikes, and slow frictional waves by visual inspection, and show that the surfaces have different behaviors depending on normal force and speed. In a second experiment, participants (10) were asked to discriminate pairs of those surfaces. It is found that each of those pairs could be reliably discriminated by most participants.

Finally, the participant's discrimination performance is correlated with differences in the physical attributes observed against the mock finger. The authors found a positive correlation between participants' performances and differences in the count of steady sliding against the mock finger and a negative correlation between participants' reaction time and differences in the count of stiction spikes against the mock finger. They

interpret those correlations as evidence that participants use those differences to discriminate the surfaces.

Strengths:

The created surfaces are very interesting as they are flat at the nanometer scale, yet have different physical attributes and can be reliably discriminated."

We thank Reviewer 2 for their notes on our manuscript. The responses below address the reviewer's comments and recommendations for revised work.

Weaknesses:

Comment 1

In my opinion, the data presented in the paper do not support the conclusions. The conclusions are based on a correlation between results obtained on the mock finger and results obtained with human participants but there is no evidence that the human participants' fingertips will behave similarly to the mock finger during the experiment. Figure 3 gives a hint that the 3 sliding behaviors can be observed in a real finger, but does not prove that the human finger will behave as the mock finger, i.e., there is no evidence that the phase maps in Figure 1C are similar for human fingers and across different people that can have very different stiffness and moisture levels.

The mechanical characterization conducted with the mock finger seeks to extract significant features of friction traces of a set of surfaces to use as predictors of tactile discriminability. The goal is to find a consistent method to characterize surfaces for use in tactile experiments that can be replicated by others and used prior to any human experiments. However, in the overall response and in a response to a similar comment by Reviewer 1, we also explain why we believe experiments on humans to establish this fact is not yet reasonable.

Comment 2

I believe that the authors collected the contact forces during the psychophysics experiments, so this shortcoming could be solved if the authors use the actual data, and show that the participant responses can be better predicted by the occurrence of frictional instabilities than by the usual metrics on a trial by trial basis, or at least on a subject by subject basis. I.e. Poor performers should show fewer signs of differences in the sliding behaviors than good performers.

To fully implement this, a decision-making model is necessary because, as a counter example, a participant could have generated 10 swipes of SFW and 1 swipe of a Sp, but the Sp may have been the most important event for making a tactile decision. This type of scenario is not compatible with the analysis suggested — and similar counterpoints can be made for other types of seemingly straightforward analysis.

While we are interested and actively working on this, the study here is critical to establish types of evidence for a future decision-making model. We know humans change their friction constantly during real exploration, so it is unclear which of these constantly changing values we should input into the decision making model, and the future challenges we anticipate are explained in Comment 1.

Comment 3

The sample size (10) is very small.

We recognize that, with all factors being equal, this sample size is on the smaller end. However, we emphasize the degree of control of samples is far above typical, with minimal variations in sample properties such as surface roughness, and every sample for every trial was pristine. Furthermore, the sample preparation (> 300 individual wafers were used) and cost became a factor. Although not typically appropriate, and thus not included in the manuscript, a post-hoc power analysis for our 100 trials of our pair that was closest to chance, P4, (53%, closest to chance at 33%) showed a power of 98.2%, suggesting that the study was appropriately powered.

Reviewer 2 (Recommendations for the authors):

Comment 1

Differences in SS and Sp (Table 2) are NOT physical or mechanical differences but are obtained by counting differences in the number of occurrences of each sliding behavior. It is rather a weird choice.

We disagree that differences in SS and Sp are not physical or mechanical, as these are well-established phenomena in the soft matter and tribology literature(19-21). These are known as “mechanical instabilities” and generated due to the effects of two physical phenomena: the elasticity of the finger (which is constant in our mechanical testing) and the friction forces present (which change per sample type). The motivation behind using these different shapes is that the instabilities, in some conditions, can be invariant to external factors like velocity. This would be quite advantageous for human exploration because, unlike friction coefficient, which changes with nearly any factor, including velocity and mass, the instabilities being invariant to velocity would mean that we are accurately characterizing a unique identifier of the surface even though velocity may be variable.

This “weird choice” is the central innovation of this paper. This choice was necessary because we demonstrated that the common usage of friction coefficient is fundamentally flawed: we see that friction coefficient suggests that surface which are more different would feel more similar – indeed the most distinctive surfaces would be two surfaces that are identical, which is clearly spurious. One potential explanation for why we were able to see this is effect is because our surfaces have similar (< 0.6 nm variability) roughness, removing potential confounding factors, and this type of low roughness control has not been used in tactile studies to the best of our knowledge.

Comment 2

Figures 2B-C: why are the x-data different than Table 2?

The x-data in Fig. 2B-C are the absolute differences in the number of occurrences measured for a given instability type or material property out of 144 pulls. Modeling the human participant results in our GLMMs required the independent variables to be in this form rather than percentages. We initially chose to list percent differences in Table 2 to highlight the ranges of differences instead of an absolute value, but have added both for clarity.

Our changes to the manuscript (Page 7)

“To determine if humans can detect these three different instabilities, we selected six pairs of surfaces to create a broad range of potential instabilities present across all three types. These are summarized in Table 2, where the first column for each instability is the difference in occurrence of that instability formed between each pair, and the second is the percent difference.”

Comment 3

"We constructed a set of coated surfaces with physical differences which were imperceptible by touch but created different types of instabilities based on how quickly a finger is slid and how hard a human finger is pressed during sliding." Yet, in your experiment, participants could discriminate them, so this is incoherent.

To clarify the point, macroscopic objects can differ in physical shape and in chemical composition. What we meant was that the physical differences, i.e., roughness, were below a limit (Skedung et al.) that participants, without a coating, would not be able to tell these apart(22). Therefore, the reason people could tell our surfaces apart was due to the chemical composition of the surface, and not any differences in roughness or physical effects like film stiffness (due to the molecular-scale thinness of the surface coatings, they are mechanically negligible). However, we concede that at the molecular scale, the traditional macroscopic distinction between physical and chemical is blurred.

We have made minor revisions to the wording in the abstract. We clarify that the surface coatings had physical differences in roughness that were smaller than 0.6 nm, which based purely on roughness, would not be expected to be distinguishable to participants. Therefore, the reason participants can tell these surfaces apart is due to differences in friction generated by chemical composition, and we were able to minimize contributions from physical differences in the sample our study.

Our changes to the manuscript (Page 1, Abstract)

"We constructed a set of coated surfaces with minimal physical differences that by themselves, are not perceptible to people, but instead, due to modification in surface chemistry, the surfaces created different types of instabilities based on how quickly a finger is slid and how hard a human finger is pressed during sliding."

Reviewer 3 (Public review):

Strengths:

The paper describes a new perspective on friction perception, with the hypothesis that humans are sensitive to the instabilities of the surface rather than the coefficient of friction. The paper is very well written and with a comprehensive literature survey.

One of the central tools used by the author to characterize the frictional behavior is the frictional instabilities maps. With these maps, it becomes clear that two different surfaces can have both similar and different behavior depending on the normal force and the speed of exploration. It puts forward that friction is a complicated phenomenon, especially for soft materials.

The psychophysics study is centered around an odd-one-out protocol, which has the advantage of avoiding any external reference to what would mean friction or texture for example. The comparisons are made only based on the texture being similar or not.

The results show a significant relationship between the distance between frictional maps and the success rate in discriminating two kinds of surface."

We thank Reviewer 3 for their notes and interesting discussion points on our manuscript. Below, we address the reviewer's feedback and comments on related works.

Weaknesses:

Comment 1

The main weakness of the paper comes from the fact that the frictional maps and the extensive psychophysics study are not made at the same time, nor with the same finger. The frictional maps are produced with an artificial finger made out of PDMS which is a poor substitute for the complex tribological properties of skin.

A similar comment was made by Reviewers 1 and 2 and parts are replicated below. We are not claiming that our PDMS fingers are superior to real fingers, but rather, we cannot establish standards in the field by using real human fingers that vary between subjects and researchers. We believe the mock finger we designed is a reasonable mimic of the human finger by matching surface energy, heterogeneous mechanical structure, and the ability to test multiple physiologically relevant pressures and sliding velocities.

We achieve a heterogeneous mechanical structure with the 3 primary components of stiffness of a human finger. The effective modulus of ~100 kPa, from soft tissue,^{8,9} is obtained with a 30:1 ratio of PDMS to crosslinker. The PDMS also surrounds a rigid, acrylic bone comparable to the distal phalanx, which provides an additional layer of higher modulus.¹⁰ Additionally, the 8-hour UV-Ozone treatment decreases the viscoelastic tack of the pristine PDMS by glassifying, or further crosslinking the surface of the finger,¹¹ therefore imparting greater stiffness at the surface similar to the contributions of the stratum corneum, along with a similar surface energy.¹² The finger is used at least a day after UV-Ozone treatment is completed in order for the surface to return to moderate hydrophilicity, similar to the outermost layer of human skin.¹⁶ We also discuss the shape of the contact formed. To ensure that there is minimal contribution from the slanted position of the finger, an initial contact area of 1×1 cm is established before sliding and recording friction measurements. As the PDMS finger is a soft object, the portion in contact with a surface flattens and the contact area remains largely unchanged during sliding. We recognize that it is difficult to completely control the pressure distribution due to the planar interface, but this variation is also expected when humans freely explore a surface. Finally, we consider flat vs. fingerprinted fingers. Our previous work on the role of fingerprints on friction experienced by a PDMS mock finger showed enhanced signals with the incorporation of ridges on the finger and used a rate-and-state model of a heterogeneous, elastic body to find corresponding trends.⁷ The key conclusion was that a flat finger still preserved key dynamic features, and the presence of stronger or more vibrations could result in more similar forces for different surfaces depending on the sliding conditions. We note that we have subsequently used the controlled mechanical data collected with this flat mock finger in correlations with human psychophysics in previous work, where findings from our mechanical experiments were predictive of human performance.^{3–6} Ultimately, we see from our prior work and here that, despite the drawbacks of our mock finger, it outperforms other standard characterization technique in providing information about the mesoscale that correlates to tactile perception. We have added these details to the manuscript.

We also note that an intermediate option, replicating real fingers, even in a mold, may also inadvertently limit trends from characterization to a specific finger. One of the main – and severe – limitations of using a human finger is that all fingers are different, meaning any study focusing on a particular user may not apply to others or be recreated easily by other researchers. We cannot set a standard for replication around a real human finger as that participant may no longer be available, or willing to travel the world as a “standard”. Furthermore, the method in which a single person changes their pressures and velocities as they touch a surface is highly variable. We also note that in the Summary Response, we noted that a study by Colgate et al. (IEEE ToH 2024) demonstrated that efference copies may be important, and thus constraining a human finger and replaying the forces recorded during free exploration will not lead to the participant identifying a surface with any consistency.

Thus, it is important to allow humans to freely explore surfaces, but creates nearly limitless variability in friction forces.

This is also against the backdrop that we are seeking to provide a method to characterize surfaces, which will be aided as we get closer in replicate a true human finger. Indeed, the more features we replicate, the more successful the mechanical data will be in correlating to tactile distinguishability. But reasonably, our success would be in replacing traditional characterization experiments, not in recreating the forces of an arbitrary human finger.

Our changes to the manuscript Added (Page 2-3)

“Mock finger as a characterization tool

In this work, we use a mechanical setup with a PDMS mock finger to derive tactile predictors from controlled friction traces alternative to average friction coefficients. While there is a tradeoff in selecting a synthetic finger over a more accurate, real human finger in modeling touch, our aim to design a method of mesoscale surface characterization for more successful studies on tactile perception cannot be fulfilled using one human participant as a standard. We believe that with sufficient replication of surface and bulk properties as well as contact geometry, and controlled friction measurements collected at loading conditions observed during a tactile discrimination task, we can isolate unique frictional features of a set of surfaces that do not arise from human-to-human variability.

The major component of a human finger, by volume, is soft tissue (~56%)(22), resulting in an effective modulus close to 100 kPa(23,24). In order to achieve this same softness, we crosslink PDMS in a 1×1×5 cm mold at a 30:1 elastomer:crosslinker ratio. However, two more features impart increased stiffness in a human finger. Most of this added rigidity is derived from the bone at the fingertip, the distal phalanx(23-25), which we mimic with an acrylic bone within our PDMS network. The stratum corneum, the stiffer, glassier outer layer of skin(26), is replicated with the surface of the mock finger glassified, or further crosslinked, after 8 hours of UV-Ozone treatment(27). This treatment also modifies the surface properties of the native PDMS to align with those of a human finger more closely. It minimizes the viscoelastic tack at the surface, resulting in a comparable non-sticky surface. At least one day after treatment, the finger surface returns to moderate hydrophilicity (~60°), as is typically observed for a real finger(28).

The initial contact area formed before a friction trace is collected is a rectangle of 1×1 cm. While this shape is not entirely representative of a human finger with curves and ridges, human fingers flatten out enough to reduce the effects of curvature with even very light pressures(28-30). This implies that regardless of finger pressure, the contact area is largely load-independent, which is more accurately replicated with a rectangular mock finger. It is still a challenge to control pressure distribution with this planar interface, but non-uniform pressures are also expected during human exploration.

Lastly, we consider fingerprints vs. flat fingers. A key finding of our previous work is that while fingerprints enhanced frictional dynamics at certain conditions, key features were still maintained with a flat finger(7). Furthermore, for some loading conditions, the more amplified signals could also result in more similar friction traces for different surfaces. We have continued to use flat fingers in our mechanical experiments, and have observed good agreement between these friction traces and human experiments(7,8,21,31).”

(Page 3-4, Materials and Methods)

“Mock Finger Preparation

Friction forces across all six surfaces were measured using a custom apparatus with a polydimethylsiloxane (PDMS, Dow Sylgard 184) mock finger that mimics a human finger’s

mechanical properties and contact mechanics while exploring a surface relatively closely(7,8). PDMS and crosslinker were combined in a 30:1 ratio to achieve a stiffness of 100 kPa comparable to a real finger, then degassed in a vacuum desiccator for 30 minutes. We are aware that the manufacturer recommended crosslinking ratio for Sylgard 184 is 10:1 due to potential uncrosslinked liquid residues(32), but further crosslinking concentrated at the surface prevents this. The prepared PDMS was then poured into a 1×1×5 cm mold also containing an acrylic 3D-printed “bone” to attach applied masses on top of the “fingertip” area contacting a surface during friction testing. After crosslinking in the mold at 60°C for 1 hour, the finger was treated with UV-Ozone for 8 hours out of the mold to minimize viscoelastic tack.

Mechanical Testing

A custom device using our PDMS mock finger was used to collect macroscopic friction force traces replicating human exploration(7,8). After placing a sample surface on a stage, the finger was lowered at a slight angle such that an initial 1×1 cm rectangle of “fingertip” contact area could be established. We considered a broad range of applied masses ($M = 0, 25, 75, \text{ and } 100 \text{ g}$) added onto the deadweight of the finger (6 g) observed during a tactile discrimination task. The other side of the sensor was connected to a motorized stage (V-508 PIMag Precision Linear Stage, Physikinstrumente) to control both displacement (4 mm across all conditions) and sliding velocity ($v = 5, 10, 25, \text{ and } 45 \text{ mm s}^{-1}$). Forces were measured at all 16 combinations of mass and velocity via a 250 g Futek force sensor ($k = 13.9 \text{ kN m}^{-1}$) threaded to the bone, and recorded at an average sampling rate of 550 Hz with a Keithley 7510 DMM digitized multimeter. Force traces were collected in sets of 4 slides, discarding the first due to contact aging. Because some mass-velocity combinations were near the boundaries of instability phase transitions, not all force traces at these given conditions exhibited similar profiles. Thus, three sets were collected on fresh spots for each condition to observe enough occurrences of multiple instabilities, at a total of nine traces per combination for each surface.”

Added References (Page 13)

M. Murai, H.-K. Lau, B. P. Pereira and R. W. H. Pho, *J. Hand Surg.*, 1997, 22, 935–941.

A. Abdouni, M. Djaghoul, C. Thieulin, R. Vargiolu, C. Pailler-Mattei and H. Zahouani, *R. Soc. Open Sci.*, DOI:10.1098/rsos.170321.

P.-H. Cornuault, L. Carpentier, M.-A. Bueno, J.-M. Cote and G. Monteil, *J. R. Soc. Interface*, DOI:10.1098/rsif.2015.0495.

K. Qian, K. Traylor, S. W. Lee, B. Ellis, J. Weiss and D. Kamper, *J. Biomech.*, 2014, 47, 3094–3099.

Y. Yuan and R. Verma, *Colloids Surf. B Biointerfaces*, 2006, 48, 6–12.

Y.-J. Fu, H. Qui, K.-S. Liao, S. J. Lue, C.-C. Hu, K.-R. Lee and J.-Y. Lai, *Langmuir*, 2010, 26, 4392–4399.

Comment 2

The evidence would have been much stronger if the measurement of the interaction was done during the psychophysical experiment. In addition, because of the protocol, the correlation is based on aggregates rather than on individual interactions.

Our Response: We agree that this would have helped further establish our argument, but in the overall statement and in other reviewer responses, we describe the significant challenges

to establishing this.

To fully implement this, a decision-making model is necessary because, as a counter example, a participant could have generated 10 swipes of SFW and 1 swipe of a Sp, but the Sp may have been the most important event for making a tactile decision. We also clarify that our goals are to provide a method to characterize samples to better design tactile interfaces in haptics or in psychophysical experiments.

In short, in our view, to develop a decision-making model, the challenges are as follows:

- (1) Which one, or combination of, of the multiple swipes that people make responsible for a tactile decision?
- (2) Establish what is, or may be, tactile evidence.
- (3) Establish tactile decision-making models are similar or different than existing decision-making models.
- (4) Test the hypothesis, in these models, that friction instabilities are evidence, and not some other unknown metric.
- (5) Design a task that does not require the use of subjective tactile descriptors, like “which one feels rougher”, which we see cause confusion in participants, which will likely require accounting for memory effects.
- (6) Design samples that vary in the amount of evidence generated, but this evidence cannot be controlled directly. Rather, the samples indirectly vary evidence by how likely it is for a human to generate different types of friction instabilities during standard exploration.

We elaborate these points below:

To successfully perform this experiment, we note that freely exploring humans make multiple strokes on a surface. Therefore, we would need to construct a decision-making model. It has not yet been demonstrated whether tactile decision making follows visual decision making, but perhaps to start, we can assume it does. Then, in the design of our decision-making paradigm, we immediately run into the problem: What is tactile evidence?

From Fig. 3C, we already can see that identifying evidence is challenging. Prior to this manuscript, people may have chosen the average force, or the highest force. Or we may choose the average friction force. Then, after deciding on the evidence, we need to find a method to manipulate the evidence, i.e., create samples or a machine that causes high friction, etc. We show that during the course of human touch, due to the dynamic nature of friction, the average can change a large amount and sample design becomes a central barrier to experiments. Others may suggest to immobilize the finger and applying a known force, but given how much friction changes with human exploration, there is no known method to make a machine recreate temporally and spatially varying friction forces during sliding onto a stationary finger. Finally, perhaps most importantly, in addition to mechanical challenges, a study by Liu, Colgate et al. showed that even if they recorded the friction (2D) of a finger exploring a surface and then replicated the same friction forces onto a finger, the participant could not determine which surface the replayed friction force was supposed to represent.¹ This supports that the efference copy is important, that the forces in response to expected motion are important to determine friction. Finally, there is no known method to design instabilities *a priori*. They must be found through experiments, especially since if we were to introduce, say a bump or a trough, then we bring in confounding variables to how participants tell surfaces apart.

Furthermore, even if we had some consistent method to create tactile “evidence”, the paradigm also deserves some consideration. In our experience, the 3-AFC task we perform is

important because the vocabulary for touch has not been established. That is, in 3-AFC, by asking to determine which one sample is unlike the others, we do not have to ask the participant questions like “which one is rougher” or “which one has less friction”. In contrast, 2-AFC, which is better for decision-making models because it does not include memory, requires the asking of a perceptual question like: “which one is rougher?”. In our ongoing work, taking two silane coatings, we found that participants could easily identify which surface is unlike the others above chance in a 3-AFC, but participants, even within their own trials, could not consistently identify one silane as perceptually “rougher” by 2-AFC. To us, this calls into question the validity of tactile descriptors, but is beyond the scope of the current manuscript.

This is not our only goal, but in the context of human exploration, in this manuscript here, we believed it was important to identify a mechanical parameter that was consistent with how humans explore surfaces, but was also a parameter that could characterize to some consistent property of a surface – irrespective of whether a human was touching it. We thought that designing human decision-making models and paradigms around the friction coefficient would not be successful.

Given the scope of these challenges, we do not think it would be possible to establish this conceptual sequence in a single manuscript.

Comment 3

The authors compensate with a third experiment where they used a 2AFC protocol and an online force measurement. But the results of this third study, fail to convince the relation.

With this experiment, our central goal was to demonstrate that the instabilities we have identified with the PDMS finger also occur with a human finger. Several instances of SS, Sp, and SFW were recorded with this setup as a participant touched surfaces in real time.

Comment 4

No map of the real finger interaction is shown, bringing doubt to the validity of the frictional map for something as variable as human fingers.

Real fingers change constantly during exploration, and friction is state-dependent, meaning that the friction will depend on how the person was moving the moment prior. Therefore, a map is only valid for a single human movement – even if participants all were instructed to take a single swipe and start from zero motion, humans are unable to maintain constant velocities and pressures. Clearly, this is not sustainable for any analysis, and these drawbacks apply to any measured parameter, whether instabilities suggested here, or friction coefficients used throughout. We believe the difficulty of this approach emphasizes why a standard map of characterization of a surface by a mock finger, even with its drawbacks, is a viable path forward.

Reviewer 3 (Recommendations for the authors):

Comment 1

It would be interesting to comment on a potential connection between the frictional instability maps and Schallamach waves

Schallamach waves are a subset of slow frictional waves (SFW). Schallmach waves are very specifically defined. They are a are pockets of air that form between a soft sliding object and rigid surface, and propagate rear-to-front (retrograde waves) as a soft object is slid and

buckles due to adhesive pinning. Wrinkles form at the detached portion of the soft material, until the interface reattaches and the process repeats.²³ There is typically a high burden of proof to establish a Schallamach wave over a more general slow frictional wave. We note that it would be exceedingly difficult to design samples that can reliably create subsets of SFW, but we are aware that this may be an interesting question at a future point in our work.

Comment 2

The force sensors look very compliant, and given the dynamic nature of the signal, it is important to characterize the frequency response of the system to make sure that the fluctuations are not amplified.

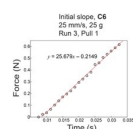
Our Response: Thank you for noticing. We mistyped the sensor spring constant as 13.9 N m^{-1} instead of kN m^{-1} . However, below we show how the instabilities are derived from the mechanics at the interface due to the compliance of the finger. The “springs” of the force sensor and PDMS finger are connected in parallel. Since $k_{\text{sensor}} = 13.9 \text{ kN m}^{-1}$, the spring constant of the system overall reflects the compliance of the finger, and highlights the oscillations arising solely from stick-slip. A sample calculation is shown below.

Author response image 1.

Fitting a line to the initial slope of the force trace for C6 gives the equation $y = 25.679_x - 0.2149$. The slope here represents force data over time data, and is divided by the velocity (25 mm/s) to determine FF the spring constant of the system $k_{\text{total}} = \frac{F}{x} = 1027.16 \text{ N/m}$. This value is lower than $k_{\text{sensor}} = 13.9 \text{ kN/m}$, indicating that the “springs” representing the force sensor and PDMS finger are connected in parallel:

$\frac{1}{k_{\text{total}}} = \frac{1}{k_{\text{sensor}}} + \frac{1}{k_{\text{finger}}}$. The finger is the compliant component of the system, with $k_{\text{finger}} = 0.902 \text{ N/m}$,

and of course, real human fingers are also compliant so this matches our goals with the design of the mock finger.



Our changes to the manuscript (Page 4)

($k = 13.9 \text{ kN m}^{-1}$)

Comment 3

The authors should discuss about the stochastic nature of friction:

Wiertlewski, Hudin, Hayward, IEEE WHC 2011

Greenspon, McLellan, Lieber, Bensmaia, JRSI 2020

We believe that, given the references, this comment on “stochastic” refers to the macroscopically-observable fluctuations (i.e., the mechanical “noise” which is not due to instrument noise) in friction arising from the discordant network of stick-slip phenomena occurring throughout the contact zone, and not the stochastic nature of nanoscale friction

that occurs thermal fluctuations nor due to statistical distributions in bond breaking associated with soft contact.

We first note that our small-scale fluctuations do not arise from a periodic surface texture that dominates in the frequency regime. However, even on our comparatively smooth surfaces, we do expect fluctuations due to nanoscale variation in contact, generation of stick-slip across at microscale length scales that occur either concurrently or discordantly across the contact zone, and the nonlinear dependence of friction to nearly any variation in state and composition(7).

Perhaps the most relevant to the manuscript is that a major advantage of analysis by friction is that it sidesteps these ever-present microscale fluctuations, leading to more clearly defined classifiers or categories during analysis. Wiertelowski et. al. showed repeated measurements in their systems ultimately gave rise to consistent frequencies(24) (we think their system was in a steady sliding regime and the patterning gave rise to underlying macroscopic waves). These consistent frequencies, at least in soft systems and absent obvious macroscopic patterned features, would be expected to arise from the instability categories and we see them throughout.

Comment 4

It is stated that "we observed a spurious, negative correlation between friction coefficient and accuracy".

What makes you qualify that correlation as spurious?

We mean this as in the statistical definition of “spurious”.

This correlation would indicate that by the metric of friction coefficient, more different surfaces are perceived more similarly. Thus, two very different surfaces, like Teflon and sandpaper, by friction coefficient would be expected to feel very similar. Two nearly identical surfaces would be expected to feel very different – but of course, humans cannot consistently distinguish two identical surfaces. This finding is counterintuitive and refutes that friction coefficient is a reliable classifier of surfaces by touch. We do not think it is productive to determine a mechanism for a spurious correlation, but perhaps one reason we were able to observe this is because our study, to the best of our knowledge, is unique for having samples that are controlled in their physical differences in roughness and surface features.

Our changes to the manuscript (Page 10)

“To compare the value of looking at frictional instabilities, we also performed GLMM fits on common approaches in the field, like a friction coefficient or material property typically used in tactile discrimination, shown in Fig. 2D-E. Interestingly, in Fig. 2D, we observed a spurious, negative correlation between friction coefficient (typically and often problematically

simplified as $F = \mu N$ across all tested conditions) and accuracy ($r = -0.64$, $p < 0.01$); that is, the

more different the surfaces are by friction coefficient, the less people can tell them apart. This spurious correlation would be the opposite of intuition, and further calls into question the common practice of using friction coefficients in touch-related studies. The alternative, two-term model which includes adhesive contact area for friction coefficient(29) was even less predictive (see Fig. S6A of SI). We believe such a correlation could not have been uncovered previously as our samples are minimal in their physical variations. Yet, the dynamic changes in force even within a single sample are not considered, despite being a key feature of mesoscale friction during human touch.

We investigate different material properties in Fig. 2E. Differences in average roughness R_a (or other parameters, like root mean square roughness R_{rms} (Fig. S6A of SI) did not show a statistically significant correlation to accuracy. Though roughness is a popular parameter, correlating any roughness parameter to human performance here could be moot: the limit of detecting roughness differences has previously been defined as 13 nm on structured surfaces(33) and much higher for randomly rough surfaces(46), all of which are magnitudes larger than the roughness differences between our surfaces. The differences in contact angle hysteresis – as an approximation of the adhesion contributions(47) – do not present any statistically significant effects on performance.”

Comment 5

The authors should comment on the influence of friction on perceptual invariance. Despite inducing radially different frictional behavior for various conditions, these surfaces are stably perceived. Maybe this is a sign that humans extract a different metric?

We agree – we are excited that frictional instabilities may offer a more stable perceptual cue because they are not prone to fluctuations (Recommendations for the authors, Comment 3) and instability formation, in many conditions, is invariant to applied pressures and velocities – thus forming large zones where a human may reasonably encounter a given instability.

Raw friction is highly prone to variation during human exploration (in alignment with Recommendations for the authors, Comment 3), but ongoing work seeks to explain tactile constancy, or the ability to identify objects despite these large changes in force. Very recently published work by Fehlborg et. al. identified the role of modulating finger speed and normal force in amplifying the differences in friction coefficient between materials in order to identify them(25), and we postulate that their work may be streamlined and consistent with the idea of friction instabilities, though we have not had a chance to discuss this in-depth with the authors yet.

We think that the instability maps show a viable path forward to how surfaces are stably perceived, and instabilities themselves show a potential mechanism: mathematically, instabilities for given conditions can be invariant to velocity or mass, creating zones where a certain instability is encountered. This reduces the immense variability of friction to a smaller, more stable classification of surfaces (e.g., a 30% SS surface or a 60% SS surface). A given surface will typically produce the same instability at a specific condition (we found some boundaries are extremely condition sensitive, but many conditions are not), whereas a single friction trace which is highly prone to variation is not a stable metric.

Added References (Page 14)

53 M. Fehlborg, E. Monfort, S. Saikumar, K. Drewing and R. Bennewitz, *IEEE Trans. Haptics*, 2024, 17, 957–963.

References

Z. Liu, J.-T. Kim, J. A. Rogers, R. L. Klatzky and J. E. Colgate, *IEEE Trans. Haptics*, 2024, 17, 441–450.

D. Gueorguiev, S. Bocheureau, A. Mouraux, V. Hayward and J.-L. Thonnard, *Sci Rep*, 2016, 6, 25553.

C. W. Carpenter, C. Dhong, N. B. Root, D. Rodriguez, E. E. Abdo, K. Skelil, M. A. Alkhadra, J. Ramirez, V. S. Ramachandran and D. J. Lipomi, *Mater. Horiz.*, 2018, 5, 70–77.

- A. Nolin, A. Licht, K. Pierson, C.-Y. Lo, L. V. Kayser and C. Dhong, *Soft Matter*, 2021, 17, 5050–5060.
- A. Nolin, K. Pierson, R. Hlibok, C.-Y. Lo, L. V. Kayser and C. Dhong, *Soft Matter*, 2022, 18, 3928–3940.
- Z. Swain, M. Derkaloustian, K. A. Hepler, A. Nolin, V. S. Damani, P. Bhattacharyya, T. Shrestha, J. Medina, L. Kayser and C. Dhong, *J. Mater. Chem. B*, DOI:10.1039/D4TB01646G.
- C. Dhong, L. V. Kayser, R. Arroyo, A. Shin, M. Finn, A. T. Kleinschmidt and D. J. Lipomi, *Soft Matter*, 2018, 14, 7483–7491.
- A. Abdouni, M. Djaghoul, C. Thieulin, R. Vargiolu, C. Pailler-Mattei and H. Zahouani, *Royal Society Open Science*, DOI:10.1098/rsos.170321.
- P.-H. Cornuault, L. Carpentier, M.-A. Bueno, J.-M. Cote and G. Monteil, *Journal of The Royal Society Interface*, DOI:10.1098/rsif.2015.0495.
- K. Qian, K. Traylor, S. W. Lee, B. Ellis, J. Weiss and D. Kamper, *J Biomech*, 2014, 47, 3094–3099.
- Y.-J. Fu, H. Qui, K.-S. Liao, S. J. Lue, C.-C. Hu, K.-R. Lee and J.-Y. Lai, *Langmuir*, 2010, 26, 4392–4399.
- Y. Yuan and R. Verma, *Colloids Surf B Biointerfaces*, 2006, 48, 6–12.
- G. Yu, J. Hu, J. Tan, Y. Gao, Y. Lu and F. Xuan, *Nanotechnology*, 2018, 29, 115502.
- L. Zheng, S. Dong, J. Nie, S. Li, Z. Ren, X. Ma, X. Chen, H. Li and Z. L. Wang, *ACS Appl. Mater. Interfaces*, 2019, 11, 42504–42511.
- K. Ma, J. Rivera, G. J. Hirasaki and S. L. Biswal, *Journal of Colloid and Interface Science*, 2011, 363, 371–378.
- A. Mavon, H. Zahouani, D. Redoules, P. Agache, Y. Gall and Ph. Humbert, *Colloids and Surfaces B: Biointerfaces*, 1997, 8, 147–155.
- E. AliAbbasi, M. Muzammil, O. Sirin, P. Lefèvre, Ø. G. Martinsen and C. Basdogan, *IEEE Trans. Haptics*, 2024, 17, 841–849.
- G. Corniani, Z. S. Lee, M. J. Carré, R. Lewis, B. P. Delhay and H. P. Saal, *eLife*, DOI:10.7554/eLife.93554.1.
- J. N. Israelachvili, *Intermolecular and Surface Forces*, Academic Press, 2011.
- S. Das, N. Cadirov, S. Chary, Y. Kaufman, J. Hogan, K. L. Turner and J. N. Israelachvili, *J R Soc Interface*, 2015, 12, 20141346.
- B. N. J. Persson, O. Albohr, C. Creton and V. Peveri, *The Journal of Chemical Physics*, 2004, 120, 8779–8793.
- L. Skedung, M. Arvidsson, J. Y. Chung, C. M. Stafford, B. Berglund and M. W. Rutland, *Sci Rep*, 2013, 3, 2617.
- K. Viswanathan, N. K. Sundaram and S. Chandrasekar, *Soft Matter*, 2016, 12, 5265–5275.
- M. Wiertelowski, C. Hudin and V. Hayward, in *2011 IEEE World Haptics Conference*, 2011, pp. 25–30.
- M. Fehlberg, E. Monfort, S. Saikumar, K. Drewing and R. Bennewitz, *IEEE Transactions on Haptics*, 2024, 17, 957–963.

<https://doi.org/10.7554/eLife.104543.1.sa0>