Predicting Materials and Their Perceptual Attributes from Tactile Signals

Li Zou, and Yasemin Vardar

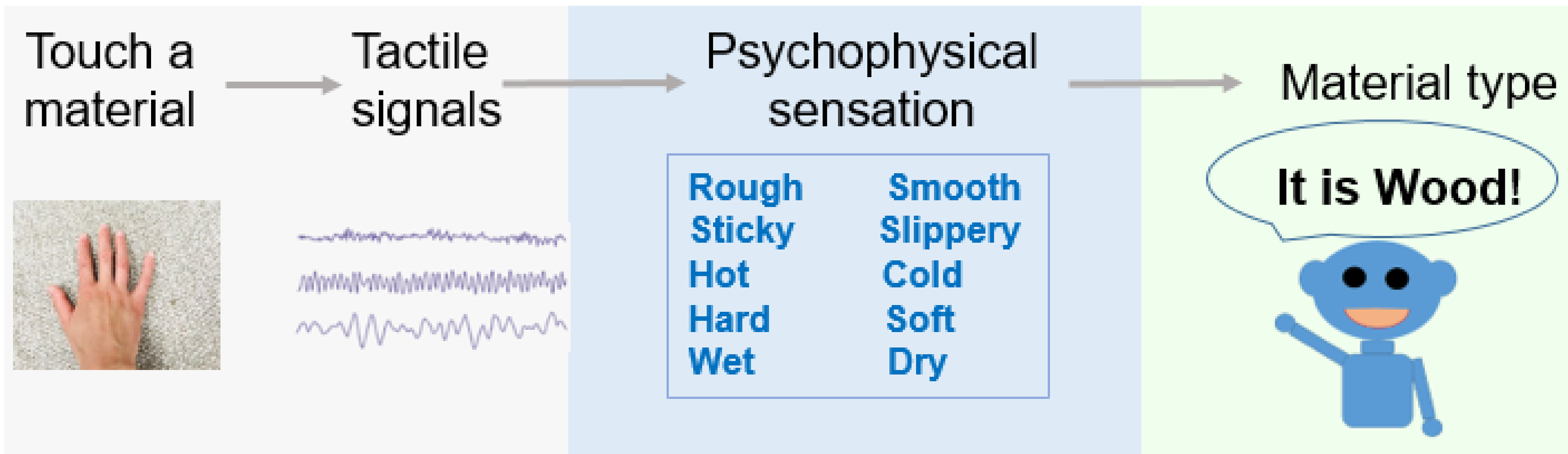
Department of Cognitive Robotics, Delft University of Technology

TU Delft HITLab

Introduction and Methodology

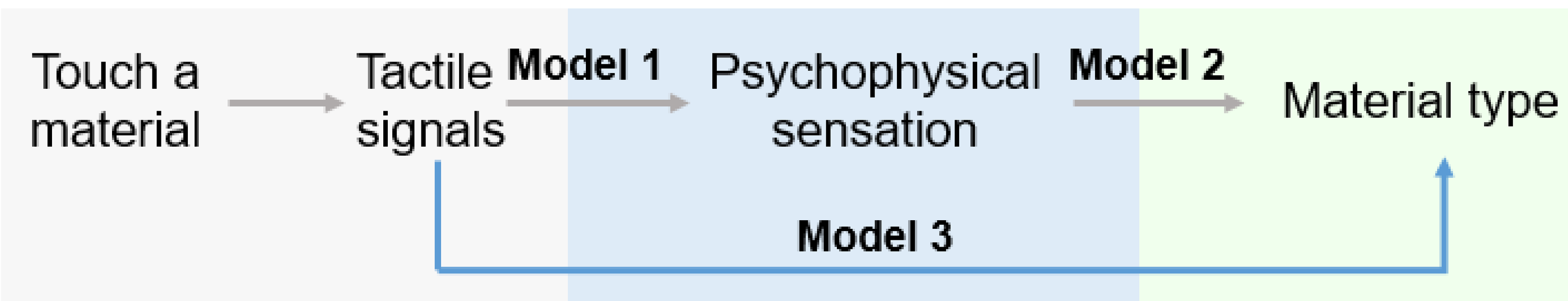
Motivation: When we touch a surface, a rich array of tactile signals is generated at the skin. These signals enable humans to perceive surface attributes such as roughness and smoothness, which in turn support material identification. However, the mechanisms by which these tactile signals are rapidly transformed into meaningful perceptual attributes—and ultimately into material recognition—remain largely unknown [1].

In this work, we employed interpretable machine learning algorithms to investigate which signal features contribute to the elicitation of perceptual attributes and the classification of materials. We further explored whether these perceptual attributes can reliably inform material recognition.

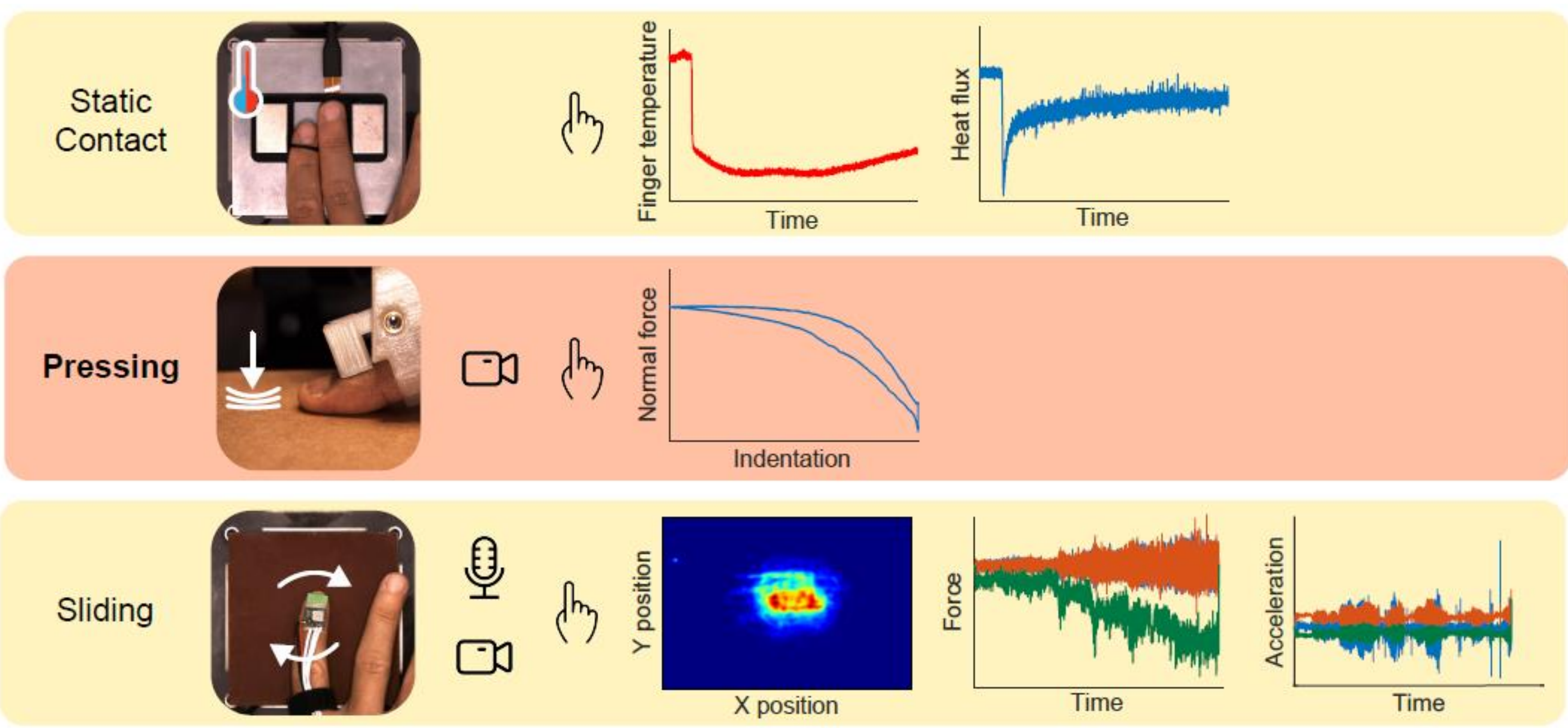


Methods: We developed three interconnected models that progressively decode tactile information.

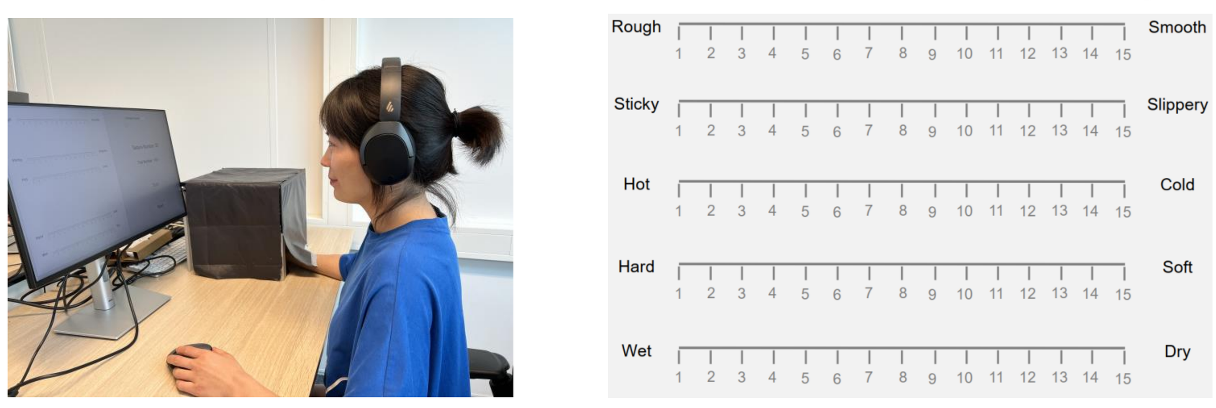
Model 1: Captures the initial stage of human perception.
Model 2: Mirrors higher-level cognitive processing.
Model 1+ Model 2: Simulates the sequential nature of human haptic perception
Model 3: Reveals the AI's inherent classification capabilities without human perceptual constraints.

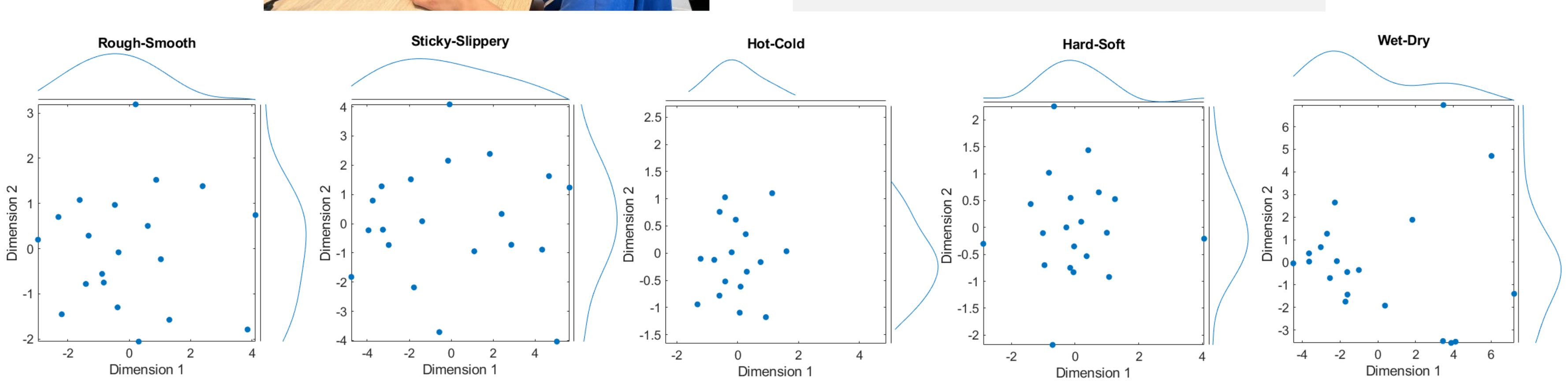


Dataset: We utilized tactile signals from the SENS3 dataset [2], which comprises multisensory data collected as two participants interacted with 50 distinct surfaces from 10 different material categories, using their bare index fingers. These interactions involved a range of exploratory procedures, including static contact, pressing, and sliding.

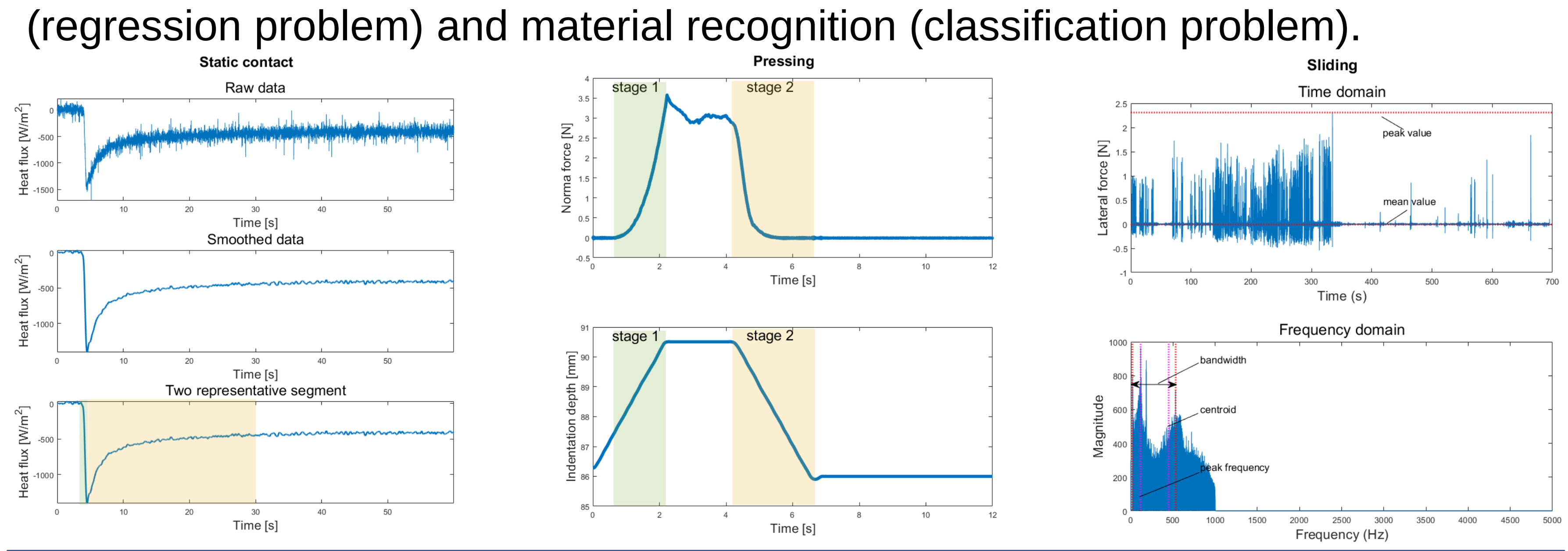


Additionally, twenty participants rated the psychophysical tactile sensations of the same surfaces through static contact, pressing, and sliding interactions. To ensure that only tactile cues were used, the textures were placed inside a box, and participants wore headphones to eliminate visual and auditory input.





Feature extraction: We extracted 59 features from the tactile data collected during static contact, pressing, and sliding interactions. They served as inputs to machine learning models designed for two tasks: sensation prediction (regression problem) and material recognition (classification problem).



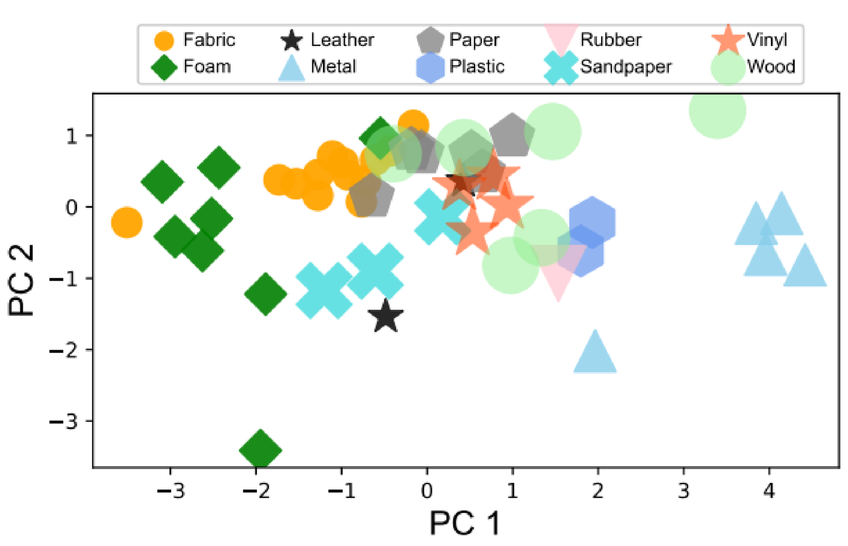
Results

When using tactile signals to predict sensation ratings, we found that features extracted from static contact were more effective for predicting sensation pair of hot–cold and hard–soft.

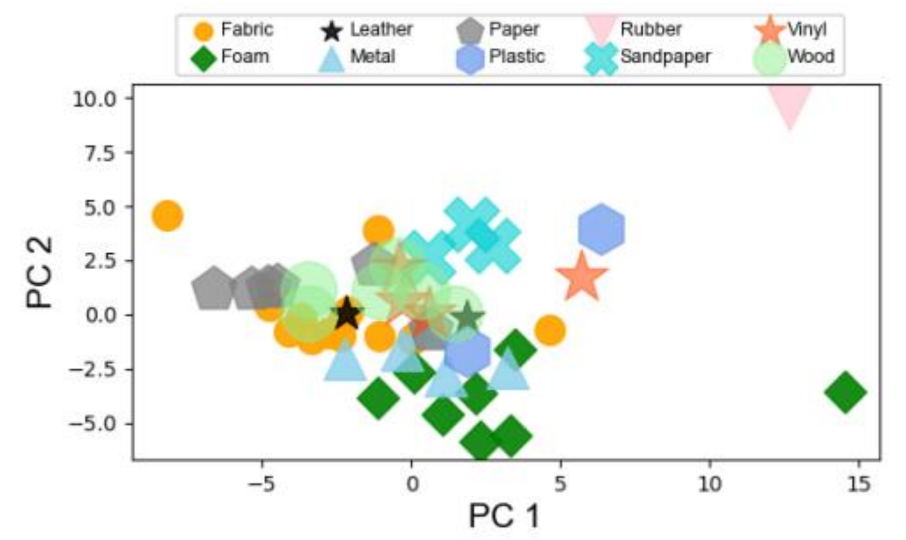
Mean squared error (MSE)					
Sensation	Null model	Static	Pressing	Sliding	All
Rough-Smooth	1.09	0.49	0.66	0.54	0.47
Sticky-Slippery	0.65	0.26	0.21	0.29	0.25
Hot-Cold	1.03	0.06	0.67	0.52	0.09
Hard-Soft	1.19	0.14	0.36	0.61	0.15
Wet-Dry	0.57	0.17	0.27	0.15	0.13
R^2					
Sensation	Null model	Static	Pressing	Sliding	All
Rough-Smooth	0	0.32	0.16	0.26	0.32
Sticky-Slippery	0	0.22	0.35	0.19	0.28
Hot-Cold	0	0.86	0.12	0.22	0.83
Hard-Soft	0	0.78	0.47	0.26	0.77
Wet-Dry	0	0.33	0.08	0.35	0.43

We achieved high classification accuracy using both sensation ratings and tactile signals. The Random Forest algorithm performed particularly well on both types of data. Again, features extracted from static contact proved to be the most effective for material classification.

Materials in sensation space



Materials in signal feature space



Models	Sensation to material	Tactile to material			
	Sensation	Static	Pressing	Sliding	All
Null model 1	0.14	0.14	0.14	0.14	0.14
Null model 2	0.18	0.18	0.18	0.18	0.18
BaggingClassifier	0.69	0.90	0.39	0.40	0.86
RandomForest	0.73	0.90	0.41	0.46	0.85
SVM	0.69	0.79	0.38	0.35	0.69
BernoulliNB	0.47	0.67	0.43	0.41	0.67
LogisticRegression	0.71	0.76	0.38	0.38	0.66
NearestCentroid	0.68	0.80	0.36	0.42	0.66
KNN	0.69	0.75	0.42	0.35	0.65
MLPClassifier	0.74	0.81	0.45	0.39	0.65
GaussianNB	0.77	0.83	0.34	0.29	0.64
GradientBoosting	0.68	0.69	0.37	0.33	0.63

References

[1] B. Richardson, Y. Vardar, C. Wallraven, and K. Kuchenbecker, "Learning to feel textures: Predicting perceptual similarities from unconstrained finger-surface interactions," *IEEE Transactions on Haptics*, vol. 15, no. 4, pp. 705–717, 2022.

[2] J. K. Balasubramanian*, B. L. Kodak*, and Y. Vardar, "SENS3: Multisensory Database of Finger-Surface Interactions and Corresponding Sensations," *in Haptics, ser. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 1. Springer, 2025, pp. 262–277