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Predicting materials and their perceptual attributes from tactile signals

Li Zou and Yasemin Vardar

I. Introduction

When humans interact with a natural surface through exploratory motions, such as sliding or pressing, a diverse range of tactile signals is generated at the skin [1]. Through these signals, humans gauge multi-dimensional attributes of the surfaces, such as smoothness, coldness, and softness, which results in material recognition (see Fig. 1a). However, how the information from these tactile signals rapidly transforms into meaningful perceptual attributes and subsequently into material recognition within the human cognitive process remains poorly understood. This limited understanding of how the brain distills and processes information from exploratory motion to recognize textures poses a key challenge in digitizing tactile information [2].

This research seeks to fill this research gap by identifying materials and perceptual attributes from tactile signals—recorded finger-surface interaction data—using Artificial Intelligence (AI) models. While existing AI models demonstrate impressive accuracy in classifying materials and can provide some interpretability into their decision-making processes,their underlying assumptions may not necessarily align with human haptic perception. Our work introduces a methodology that develops AI systems capable of not only identifying materials from tactile signals but also mimicking humans' haptic perception process (see Fig. 1b).

Our approach involves developing three interconnected models that progressively decode tactile information. Model 1 establishes the foundational mapping between raw tactile signals and psychophysical sensation ratings, capturing the initial stage of human perception. Building on this, Model 2 translates these attributes into material classifications, mirroring higher-level cognitive processing. For comparison, Model 3 implements an end-to-end approach that directly associates tactile signals with material categories. This tripartite architecture serves dual purposes: the combined Models 1 and 2 will simulate the sequential nature of human haptic perception, while Model 3 will reveal the AI's inherent classification capabilities without human perceptual constraints.

II. Methods

A. Dataset

The tactile signals used in our study was obtained from SENS3, an open-access multisensory dataset collected from fifty different surfaces [3]. The data was collected using a

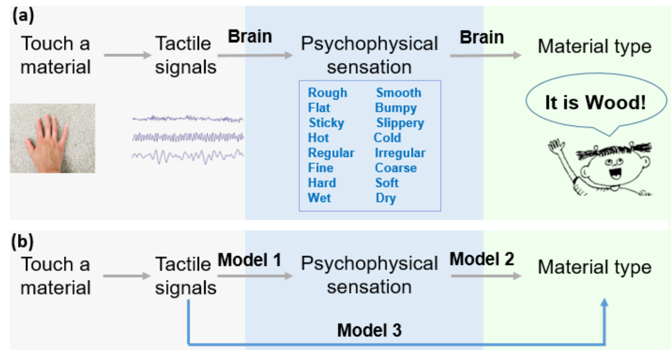

Fig. 1. Illustration of the material recognition process in humans and our algorithm. (a) Humans perceive tactile signals that convey multisensory surface attributes, resulting in material recognition. (b) Our approach models this process by developing three AI algorithms that identify materials from tactile signals and mimic the underlying human tactile perception process.

multi-sensory apparatus equipped with an accelerometer, a force sensor, a thermistor, a heat-flux sensor, an infrared position sensor, a camera, and a microphone. Two participants explored these surfaces with their fingertips using various actions, including static contact, pressing, and sliding. In addition, psychophysical sensation data was collected from 13 participants who rated the surfaces in 8 perceptual dimensions, such as rough-smooth, flat-bumpy, sticky-slippery, hot-cold, regular-irregular, fine-coarse, hard-soft, and wet-dry, while freely interacting with them.

B. Feature extraction

We extracted features from the finger-surface interaction data recorded during pressing, static contact, and sliding exploratory actions to capture the intrinsic properties of materials.

For pressing and lifting, we used the maximum indentation depth and its rate of change, capturing the variation of the indentation depth as a function of applied force. These features reflect the material's response when force is applied to its surface. Additionally, the average difference in indentation depth at the same applied force between the pressing stage and the force removal stage was calculated as a feature.

For static contact, a 4-parameter logistic regression is used to fit the recorded heatflux and skin temperature data, and the resulting parameters—the initial temperature at time zero, the steepness of the curve, the inflection point (where the curvature changes direction), and the estimated heatflux value at infinite contact time—were used as features.

For sliding, we extracted features in both the time and frequency domains for the lateral force and the accelerometer. In the time domain, the extracted features include mean, standard deviation, root mean square (RMS), maximum

The authors are with the Department of Cognitive Robotics, Delft University of Technology, Delft, The Netherlands. E-mail of authors are: L.Zou@tudelft.nl and Y.Vardar@tudelft.nl

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value, skewness, kurtosis, and the friction coefficient. These features describe the statistical and physical properties of the force signal during sliding. In the frequency domain, we computed features such as spectral centroid, spectral spread, spectral roll-off, and spectral flatness.

C. Supervised machine learning models

To identify materials from tactile signals while mimicking the human haptic perception process, we developed three models. The first model (Model 1) mapped tactile signals to psychophysical sensation ratings. The second model (Model 2) then mapped these ratings to material types. The third model (Model 3) directly mapped tactile signals to material types. Models 1 and 2 aimed to simulate the human haptic perception process, while Model 3 tested the capabilities of AI in classifying materials directly from tactile signals. The combination of Model 1 and Model 2 reveals the decision-making process of the AI model in material classification, guided by human input. In contrast, Model 3 demonstrates the decision-making process of the AI model when classifying materials independently, without human guidance.

Models 1, 2, and 3 were selected from the following machine learning algorithms to achieve the highest prediction or classification accuracy for the given task: K-Nearest Neighbors (KNN), Bagging Classifier, Logistic Regression, Multilayer Perceptron classifier, Bernoulli Naive Bayes, Gaussian Naïve Bayes, Nearest Centroid, Random Forest, Support Vector Machine, Gradient Boosting and Lasso Regression.

III. Results and Discussion

A. Mapping tactile signals to psychophysical sensations

To explore the relationship between tactile signals and psychophysical sensations, we used the features extracted in Section II-B to predict the ratings for each pair of psychophysical sensations. For this prediction task, we applied regression algorithms, such as Lasso Regression (LR) and Random Forest (RF). Prediction performance was evaluated using the R-squared (R^2) metric.

As shown in Table I, not all sensation ratings were accurately predicted using our current data. Among the data types, thermal data yielded the best performance, successfully predicting sensation pairs like hot-cold, hard-soft, and wet-dry. The sliding data proved effective in accurately predicting sticky-slippery and performed reasonably well for hard-soft and wet-dry classifications. Pressing data also contributed, especially in improving the prediction of hard-soft properties. When all data were combined, the model could predict all sensation pairs that were predictable using either data type individually. Interestingly, most sensations related to roughness, such as rough–smooth, flat–bumpy, regular–irregular, and fine–coarse, were not accurately predicted from sliding data, highlighting the need for further investigation.

B. Mapping psychophysical sensations to material types

This subsection focuses on evaluating the effectiveness of our psychophysical sensation data in classifying materials. It also aims to identify the optimal AI model that can best capture the relationship between psychophysical sensations and material types. As shown in the first column of Table II, the collected sensation ratings were effective in predicting material types. Among the models tested, Logistic Regression, MLP Classifier, and SVM demonstrated the highest prediction accuracy.

TABLE I
THE R-SQUARED SCORE FOR THE REGRESSION. THE BEST POSSIBLE SCORE IS 1.0, WHILE THE WORST IS 0.

Sensation Pairs	Model	Pressing	Thermal	Sliding	All
Rough-Smooth	LR	0	0.14	0	0
Rough-Smooth	RF	0	0	0	0
Flat-Bumpy	LR	0	0	0	0
Flat-Bumpy	RF	0	0	0	0
Sticky-Slippery	LR	0	0	0.66	0.66
Sticky-Slippery	RF	0.16	0.46	0.84	0.82
Hot-Cold	LR	0	0.96	0.12	0.97
Hot-Cold	RF	0	0.95	0.19	0.91
Regular-Irregular	LR	0	0	0	0
Regular-Irregular	RF	0	0	0	0
Fine-Coarse	LR	0	0	0	0.04
Fine-Coarse	RF	0	0	0	0
Hard-Soft	LR	0.40	0.71	0.53	0.93
Hard-Soft	RF	0.56	0.92	0.61	0.96
Wet-Dry	LR	0	0.79	0.36	0.83
Wet-Dry	RF	0	0.82	0.29	0.63

TABLE II
THE ACCURACY (THE PROPORTION OF ALL CLASSIFICATIONS THAT ARE CORRECTLY IDENTIFIED) FOR MATERIAL CLASSIFICATION.

Models	Sensation to type	Tactile signals to type
KNN	0.8	0.7
BaggingClassifier	0.7	1
LogisticRegression	0.9	0.8
MLPClassifier	0.9	0.9
BernoulliNB	0.8	0.7
GaussianNB	0.8	0.8
NearestCentroid	0.7	0.7
RandomForest	0.7	1
SVM	0.9	0.8
GradientBoosting	0.8	0.7

C. Mapping tactile signals to material types

From Table II (2nd column), we can see that most AI models achieved excellent accuracy in material classification when tactile signal data was provided.

In conclusion, the results demonstrate that our models have significant potential in predicting sensation ratings and material classification. Moving forward, we will focus on examining the differences between the models, feature importance, and their decision-making processes.

References

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