Image-Based Tactile Sensing of Macroscopic Surface Roughness Enhanced by Multi-Force Integration

Muhammad Irwan Yanwari
Dept. Computer Engineering Technology, Polines
Semarang, Indonesia
Dept. Computer Science, Tokyo Metropolitan University
Tokyo, Japan

Shogo Okamoto
Dept. Computer Science, Tokyo Metropolitan University
Tokyo, Japan
okamotos@tmu.ac.jp

***Abstract*—Tactile texture sensors aim to estimate how product surfaces feel to human touch. A promising approach to designing such sensors is to emulate the human texture-sensing process. In this study, we refine a previously developed image-based tactile sensor for evaluating macroscopic surface roughness. The sensor estimates perceived roughness by analyzing the spatial frequency spectrum of the contact area—based on the spatial coding mechanism of human tactile perception—between a transparent, compliant, finger-like pad and textured surfaces. We demonstrate that incorporating contact images captured under multiple pressing-force levels (0.5–3.0 N) improves the sensor's prediction of subjective roughness perception by approximately 21%. Moreover, the combined multiple force levels shows that stronger forces consistently have greater importance. These findings offer new insights into the design of tactile sensing systems that more closely align with human haptic experience.**

***Index Terms*—partial least squares regression, texture, spatial coding.**

I. Introduction

Tactile sensors are designed to measure the topographical, mechanical, and thermal properties of object surfaces that determine how they feel to the touch. Many existing tactile sensors for surface roughness rely on vibrations generated when a sensor probe rubs against a surface [1]. This approach resembles the temporal coding mechanism that humans use to perceive fine (microscopic) surface textures [2], [3].

In contrast, humans also rely on a different mechanism—spatial coding—to perceive macroscopic surface roughness. This mechanism is based on the spatial distribution of activated pressure sensitive neural units beneath the fingertip skin, which arises from contact between the finger pad and a textured surface [2], [4], [5]. There have been few tactile sensors that estimate perceived roughness based on the spatial coding principle.

To address this gap, we previously developed a sensor system that estimates perceived macroscopic roughness by analyzing images of the contact area formed when a transparent, compliant artificial fingertip touches a textured surface [6]. The aim of the present study is to improve the estimation accuracy of this system. To this end, we integrate contact area images captured under multiple levels of contact force. We then assess whether roughness estimation based on integrated information surpasses estimation using single-force data and evaluate the contribution of each pressing force to the overall performance based on the variable importance in projection (VIP) score.

This research was in part funded by MEXT Kakenshi #24K03019.

II. Specimens

Two types of rigid grating roughness specimens, manufactured using Tough Resin V5 (Formlabs Inc., Somerville), were used in this study. Each specimen was 20 mm in height, 50 mm in length, and 10 mm in width, as illustrated in Fig. 1(a). The two types were circular (C-type) and rectangular (R-type). Both types featured seven levels of surface wavelength, ranging from 2.0 to 5.0 mm in 0.5 mm increments.

Subjective roughness values were collected using the psychophysical method of magnitude estimation from 10 participants [6]–[8]. Roughness was measured relative to a rectangular specimen with a 3-mm wavelength. The mean subjective roughness values ranged from 0.37 to 1.72 across the specimens.

III. Apparatus

The experimental setup is shown in Fig. 1(b). It consists of an image capture device (L-836 Camera with L-600 Lens, Hozan Co. Ltd., Japan), a transparent plastic pad (Plastic Worm, Two-L Co., Ltd., Japan) with fingerprint-like patterns serving as the sensor body, a Z-axis stage for applying normal force, and a digital scale for measuring the applied force. The roughness specimen was pressed against the surface of the compliant pad, and the contact area was imaged from an angled direction through the transparent material.

IV. Method

A. Contact Images between Specimens and Compliant Pad

For each specimen and pressing force (0.5 N, 1 N, 2 N, and 3 N), 10 images were captured and processed using grayscale filtering. For each image, the amplitude spectrum was computed via Fourier transform. The spectral amplitudes

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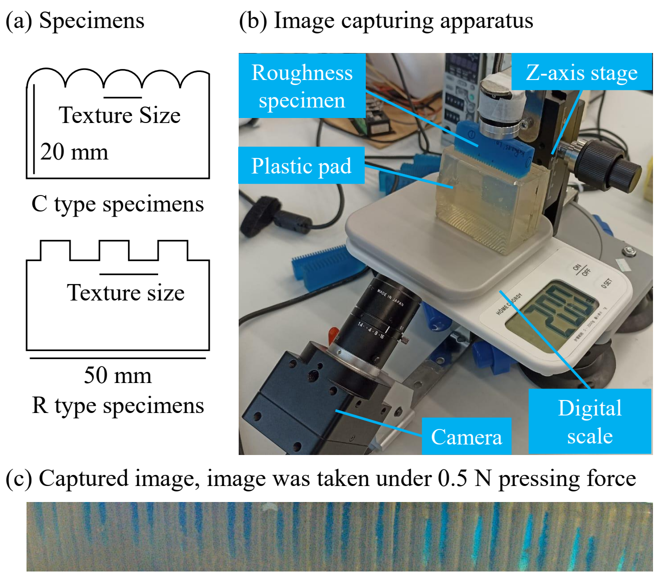

Fig. 1. Data collecting apparatus and the specimen specifications. Adapted from [6].

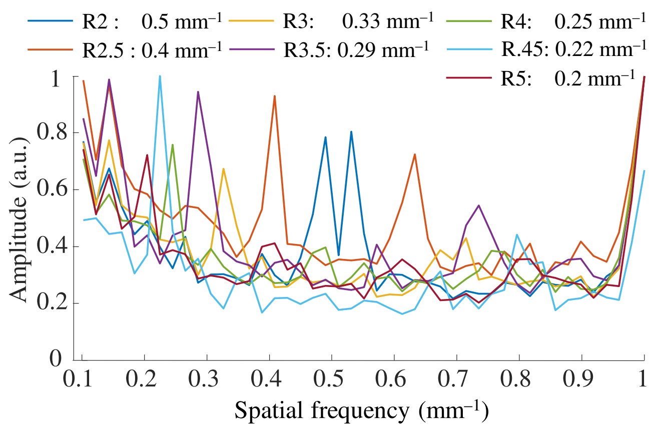

Fig. 2. Amplitude spectra from rectangular specimens with 0.5 N pressing force. Each curve contains 45 data points. Ra denotes a specimen with a texture size of a mm.

were then normalized such that the areas under the curves were equal across all the images. This process resulted in 140 (14 specimens × 10 images) datasets per pressing force with 45 discrete frequency components for each dataset as shown in Fig. 2. All processing was performed using MATLAB (2024a, MathWorks, Inc., Massachusetts).

B. Prediction Model

Subjective roughness was predicted by linearly combining 45 amplitude values extracted from each contact image. A Partial Least Squares (PLS) regression model, based on the 'plsregress' function in MATLAB, was then applied across fifteen force-level combinations [9]. For each combination, leave-one-out cross-validation was used to identify the optimal number of principal components. Model performance was

TABLE I
PREDICTION PERFORMANCE AND CONTRIBUTION OF EACH PRESSING FORCE DURING THE APPLICATION OF MULTIPLE PRESSING FORCES

Used datasets	RMSE	PC	VIP Scores			
			0.5 N	1 N	2 N	3 N
0.5 N	0.29	5	0.74	-	-	-
1 N	0.25	6	-	0.75	-	-
2 N	0.24	7	-	-	0.78	-
3 N	0.24	8	-	-	-	0.78
0.5 & 1 N	0.24	7	0.47	0.95	-	-
0.5 & 2 N	0.23	8	0.40	-	1.02	-
0.5 & 3 N	0.23	15	0.40	-	-	1.04
1 & 2 N	0.22	7	-	0.64	0.88	-
1 & 3 N	0.21	10	-	0.59	-	0.92
2 & 3 N	0.22	9	-	-	0.72	0.83
0.5, 1 & 2 N	0.22	8	0.38	0.74	1.03	-
0.5, 1 & 3 N	0.21	11	0.35	0.70	-	1.10
0.5, 2 & 3 N	0.21	20	0.36	-	0.85	1.00
1, 2 & 3 N	0.21	10	-	0.60	0.78	0.91
0.5, 1, 2 & 3 N	0.20	10	0.33	0.66	0.88	1.04

assessed using the root mean squared error (RMSE) between predicted and subjective roughness values.

To quantify the contribution of each pressing force, the variable importance in projection (VIP) score was calculated for each predictor [10]. To determine the contribution of each pressing force, the predictor scores within the same pressing force group were averaged.

V. RESULTS

Table I presents the contributions of each predictor group, categorized by pressing force. The first column specifies the pressing force used in each prediction model, and the second column reports the corresponding RMSE values. The third column indicates the optimal number of principal components (PC) determined via cross-validation. Columns four through seven detail the relative contributions of each pressing force to the prediction outcomes based on VIP Scores.

Based on the RMSE results, the model utilizing all four pressing forces—0.5 N, 1 N, 2 N, and 3 N—achieved the lowest RMSE of 0.20. In contrast, models using only a single pressing force (i.e., 0.5 N, 1 N, 2 N, or 3 N individually) exhibited RMSE values ranging from 0.24 to 0.29. This corresponds to a performance improvement ranging from approximately 16% to 31%, with an average improvement of 21% across all single-force scenarios. Among the four pressing forces, 0.5 N contributed the least to the predictive performance, with an average VIP score of 0.43. In contrast, the 3 N pressing force demonstrated the highest contribution, with an average VIP score of 0.95.

VI. DISCUSSIONS

Overall, the RMSE values was ranged from 0.29 to 0.20. As anticipated, the single pressing force prediction at 0.5 N yielded the highest RMSE of 0.29, reflecting the difficulty in capturing adequate spatial information with a light touch—similar to the challenge humans face when making roughness judgments with minimal contact.

Two notable trends emerged from the results. First, an increase in the number of predictors was associated with a gradual reduction in RMSE, suggesting that incorporating additional pressing force levels may enhance predictive accuracy. Second, the inclusion of higher pressing forces led to a decline in the relative contribution of lower-force spectra, while the overall importance of each force level within the model increased proportionally with its magnitude when more than two force levels were combined.

In this study, the range of applied pressing forces (0.5–3.0 N) was empirically selected to balance practical contact intensities with participant comfort [6]. While higher forces may enhance image clarity and spatial contrast—mirroring characteristics of the human sensory system [11]—they also pose risks. Excessive force can physically damage the sensor body, much like the point at which pressing intensity exceeds the human threshold for strain or discomfort.

Future research could investigate dynamically varying pressing forces—mimicking the fluctuations characteristic of human exploratory behavior—to assess how these force changes improve the estimation of texture roughness.

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