Modeling Perceived Roughness Based on Deformation Analysis of the Fingerpad

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I. INTRODUCTION

Tactile perception is one of the five senses, enabling the recognition of external environments through skin contact. With the advancement of virtual reality (VR), the development of tactile and haptic devices has attracted interest for enhancing user immersion. However, development of these devices often relies on repeated prototyping and user testing, which can be time-consuming. This makes entire development process longer and complicated. Simulating mechanical stimuli and predicting tactile sensations computationally could improve development efficiency. Among tactile qualities, roughness perception plays a key role in daily interactions-helping us judge surface texture, material properties, and comfort in wearable items. If the roughness can be estimated via a calculation, it will be possible to design better tactile devices for VR environments and evaluate the texture of products in a short time without conducting user experiments.

This study takes a first step toward estimating perceived roughness without user experiments by exploring effective features. In particular, we investigate whether features extracted from strain energy density (SED) time-series data —obtained via finite element analysis while tracing textured surfaces—can effectively predict subjective roughness ratings [1].

II. FINITE ELEMENT MODEL OF A FINGER

Fig. 1 shows the 3D finite element model of a human finger used to analyze skin deformation. The model consists of five layers: bone, subcutaneous tissue, dermis, epidermis, and nail. The epidermis and dermis are set to 0.7 mm and 1.8 mm thick, respectively. All layers are modeled as linear elastic materials, with mechanical properties referenced from previous studies [2] [3], as listed in TABLE I.

Layers except the epidermis are meshed with tetrahedral elements of approximately 1 mm, while the epidermis, in contact with textured surfaces, is meshed with finer elements of approximately 0.1 mm. The model comprises 147,435 elements and 32,804 nodes. Simulations were conducted using the nonlinear finite element software (Marc/Mentat, Hexagon).



Fig. 1. Structure of 3D finger model.

TABLE I MATERIAL PROPERTIES OF EACH LAYER IN THE FINGER MODEL.

layer	Young's modulus (Mpa)	Poisson ratio
bone	1.7×10^{4}	0.30
subcutaneous tissue	3.4×10^{-2}	0.48
dermis	8.0×10^{-2}	0.48
epidermis	2.0	0.30
nail	$1.7 imes 10^2$	0.30

III. EXPERIMENT

A. Simulation

As shown in Fig. 2, a contact analysis is performed between the 3D finger model and a textured surface, following the experimental conditions described by Blake et al. [1]. The surface consists of truncated conical protrusions arranged in a square grid at 3.5 mm intervals. The diameter and height of the protrusions vary from 0.70 to 2.5 mm and 0.28 to 0.62 mm, respectively. The surface is pressed vertically against the fingertip for 0.1 s until a displacement of 1.8 mm is reached, then slid horizontally at 30 mm/s for 0.5 s while maintaining the same displacement. The surface is assumed to be rigid and smooth, with a friction coefficient of 0.4, based on Sivamani 's study [4]. The total simulation time (0.6 s) is divided into 600 steps. For regression analysis,



Fig. 2. Finite element analysis of the finger model and the textured surface model

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Fig. 3. Time-series data of SED with a constant protrusion height and varying diameters (indicated in the legend).

SED is recorded from a single node at the dermis–epidermis boundary in the fingertip region.

B. Regression analysis

Multiple linear regression models the relationship between fingertip deformation and extracted features. The explanatory variables are features derived from the time-series data of SED obtained via finite element analysis. The target variable is the roughness rating from Blake et al.'s experiment [1]. Psychophysical data from 15 participants were normalized by dividing each response by the participant's overall mean, then averaged per surface and across participants. Features were computed from the original SED time-series data fand its first (f') and second (f'') derivatives. For each, the maximum (max), minimum (min), mean (mean), and standard deviation (s) are calculated, resulting in 12 features in total. To prevent overfitting, regression models are built using all 220 combinations of 3 out of 12 features. The coefficient of determination (R^2) is computed for each, and the frequency of features appearing in models with $R^2 \ge 0.9$ is counted.

IV. RESULT

A. Simulation

Fig. 3 shows the SED time-series data when in contact with textured surfaces having the same protrusion height but different diameters. As the diameter increases, the SED at the waveform peaks decreases, likely due to the larger contact area dispersing the force. Fig. 4 shows the SED timeseries data when in contact with textured surfaces having the same diameter but different heights. As the height increases, the SED at the peaks increases, likely due to the larger displacement of the protrusions causing greater deformation.

B. Regression analysis

Among all combinations of three features selected from the 12 candidates, the highest R^2 was achieved using the mean, standard deviation, and maximum of the original timeseries data: mean(f), s(f), and max(f). Table II summarizes the frequency of feature occurrences in models with $R^2 \ge$ 0.9 out of the 220 combinations. The most frequent feature was mean(f), appearing 51 times, followed by s(f) (44 times) and s(f') (28 times). These results indicate that high- R^2 models often include features representing the average



Fig. 4. Time-series data of SED with a constant protrusion diameter and varying heights (indicated in the legend).

TABLE II FREQUENCY OF FEATURE OCCURRENCES.

Feature	Count
mean(f)	51
$\mathbf{s}(f)$	44
$\max(f)$	23
$\min(f)$	17
mean(f')	16
s(f')	28
$\max(f')$	20
$\min(f')$	16
mean(f'')	13
$s(f^{\prime\prime})$	20
$\max(f'')$	17
$\min(f'')$	20

deformation, its variability, and the variability of deformation velocity. There was a strong negative correlation (r <-0.9) between the protrusion diameter and both the mean and standard deviation. These features may play an important role in enhancing the accuracy of the prediction.

V. CONCLUSION

This study examined which features extracted from SED time-series data during fingertip deformation contribute to roughness perception. High- R^2 models frequently included the mean and standard deviation of the SED. This may be attributed to the simplicity and periodicity of the surface pattern used in this study. For irregular surface patterns, direct analysis of the time-series using recurrent neural networks may be more effective. Future work will focus on data augmentation to build more generalizable models.

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