2025 IEEE World Haptics Conference (WHC)
Suwon Convention Center, Suwon, Korea
July 8 ~ 11, 2025

Spectral shape-based low-parameter texture representations

Jagan K. Balasubramanian and Yasemin Vardar

I. Introduction

Touchscreens are widely used in modern devices but often lack tactile feedback, limiting the ability to convey the sense of touch for digital objects. Surface haptic technologies—particularly electrovibration—offer a promising solution for this challenge. Electrovibration occurs when a high-voltage signal is applied to a conductive surface with a dielectric layer, such as a capacitive touchscreen, generating an electric field that induces an attractive force between the finger and the screen. By modulating this force, different texture sensations can be simulated on touchscreens through frictional variations perceived during finger movement.

While electrovibration can potentially recreate the real textures feel on touchscreens, it is limited by a large number of real-world textures. Natural bare-finger interactions with real surfaces produce rich frictional signals, which are attempted to be replicated via electrovibration displays with the recorded friction signals as voltage inputs. However, capturing raw friction data for every possible surface is costly and labor-intensive, requiring specialized equipment and significant manual effort. Moreover, these recorded signals often contain perceptually redundant information and vary depending on the finger's normal force and exploration speed. Accounting for these dynamic variations adds another layer of complexity to accurately reproducing texture sensations. Consequently, researchers are exploring ways to parameterize the recorded interaction signals, aiming to simplify the texture rendering and enable the generation of novel textures from compact, interpretable representations.

Early texture modeling studies used autoregressive (AR) coefficients to parametrize tactile interaction data [1]. However, these coefficients are specific to each texture and exploration condition, limiting the generalizability of this method for unknown surfaces. Another approach uses Mel-frequency cepstral coefficients (MFCCs) [2] to model texture signals, offering flexibility to author new textures by interpolating the coefficients. However, MFCCs were originally designed for audio feature extraction, with frequency scales weighted according to auditory bandwidth (Mel-scale), not tactile perception. Fielder and Vardar [3] addressed this challenge by using key peak frequency components from texture spectra to recreate signals. However, the success of this method depends on the number of selected peak components, which can vary for different textures.

The authors are with the Department of Cognitive Robotics, Delft University of Technology, Delft, The Netherlands. E-mails:j.krishnasamybalasubramanian@tudelft.nl, sey.vardar@tudelft.

This work was partly funded by the Dutch Research Council (NWO) with project number 19153.

Here, we propose two new texture representations: spectral slope and beta representation (see Fig. 1). These representations address the limitations of prior techniques, which require selecting the necessary number of peak components varying for texture types [3] or rely on complex, high-dimensional data that lack generalization [1], [2]. We evaluated existing and proposed methods in terms of their ability to capture the original recordings and preserve the perceptual similarity under electrovibration. Our goal is to develop simpler, low-dimensional models that retain the perceptual essence of textures. Furthermore, we aim to understand which new representations best balance simplicity, perceptual realism, and generalizability.

II. Methods

A. Texture representations

The spectral slope method models the shape of a texture's magnitude spectrum by estimating its slope, which is then used to determine the order of low-pass and high-pass filters that together form a narrow band-pass filter centered at the spectral peak. This filter is applied to white noise to synthesize the texture signal.

The beta representation approximates the magnitude spectrum using a skewed beta distribution, reflecting the natural shape of many texture spectra. The distribution's shape parameters α and β are used to design a filter that also operates on white noise to reconstruct the signal.

B. Texture Rendering and Evaluation

We recorded finger-surface interaction data from three surfaces using a custom setup with two ATI Nano 17 TI 6-axis force sensors mounted on an aluminum base and placed on an optical table. The surfaces—sandpaper, fabric, and corrugated paper—were cut to 100×100 mm squares and adhered to an acrylic base positioned on the force sensor. The first author scanned the surfaces at a constant speed of 80 mm/s and 0.4 N force. Contact forces were recorded at 20 kHz by a PCIE-daq (NI 6323). For texture rendering, we used a 70×30 mm touchscreen (3M SCT3250) placed on force sensors, with a Tabor 9200a high-voltage power supply connected to the PCIE-daq to excite the touchscreen.

An impact hammer test characterized the setup as a fourth-order system. The recorded signals were compensated for the setup's response, bandpass filtered (20–1000 Hz), and modeled using five representation methods. The model outputs were convolved with an inverse first-order response [4] to account for finger–electrovibration behavior and later amplitude-modulated with a 7 kHz carrier after taking the envelope's square root [3].

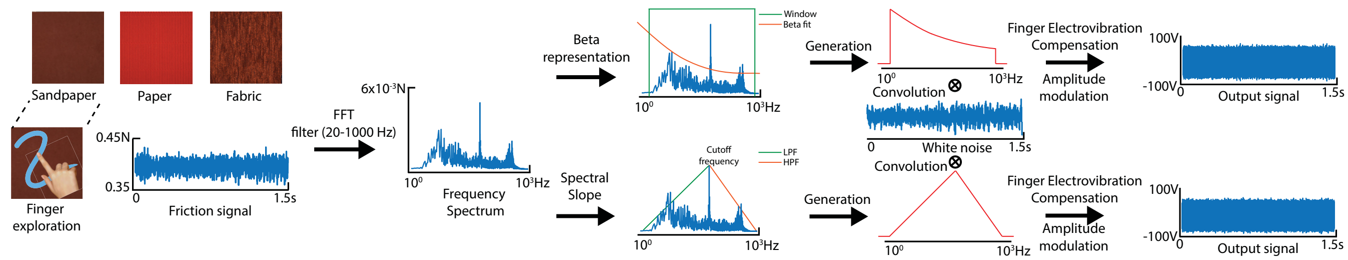

Fig. 1. Illustration of textures used in the study and their rendering process. The recorded friction signals were trimmed to 1 second, filtered, and modeled using spectral methods and beta representation. Then they were modulated for rendering on an electrovibration display.

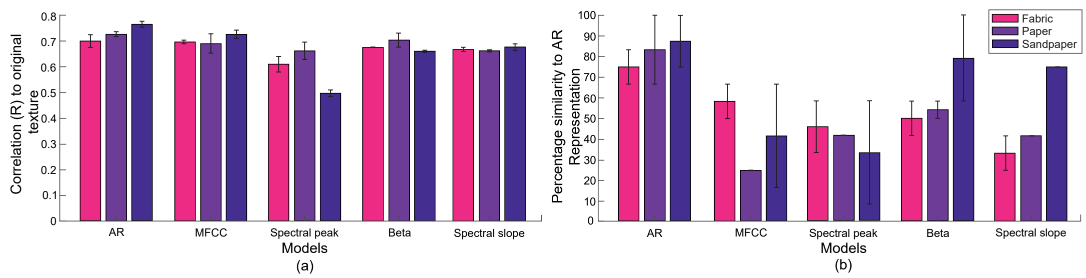

Fig. 2. Bar graphs with standard errors showing preliminary results averaged across two participants. (a) Pearson correlation between the recorded friction magnitude spectra of textures rendered using the representations and the real texture. (b) Percentage similarity of the rendered signals through selected representations—Autoregression (AR), Mel-frequency cepstral coefficients (MFCCs), Spectral Peak, Beta representation, and Spectral Slope—to the signals represented with AR. Similarity was calculated by normalizing each participant's Likert scale ratings based on their maximum score.

We first evaluated how well each texture representation captured information from the original recordings. To do this, we calculated Pearson's correlation between the magnitude spectra of the originally recorded friction signals and those generated by each representation as participants slid their fingers over the electrovibration display during rendering.

Next, we compared MFCC, spectral peak, beta representation, and spectral slope methods' ability to preserve the textures' perceptual essence, using the AR representation as a reference, as its output— before rendering— exhibited the highest spectral correlation with recordings from real surfaces. Two participants rated the similarity between textures rendered with each representation and those rendered with AR using a 7-point Likert scale. AR was also compared with itself as a control. The participant slid their index finger across the screen at 80 mm/s and 0.4 N normal force and provided a similarity rating using a 7-point Likert scale. In total, 45 trials were conducted (5 representations$\times$3 textures$\times$3 repetitions). Each trial consisted of two sections: in the first, the texture rendered with the AR representation was presented, followed by the texture rendered with one of the other methods. The order of both texture representations and textures themselves was randomized. After the experiment, the resulting similarity percentages were calculated by dividing the average Likert scale rating across repetitions by the maximum rating value.

III. Results and Discussion

Figure 2 summarizes the evaluation results. AR showed high spectral correlations ($R > 0.7$) and over 75% perceptual similarity. Slight differences in finger mechanics and exploration can explain the marginally lower correlation and similarity. MFCC had spectral correlations above 0.67 across textures, with low perceptual similarity between 25% (paper) and 57% (fabric), likely due to its mel-scaled filter banks. Spectral peak correlations ranged from 0.5 to 0.65, with low perceptual similarity between 32% (sandpaper) and 43% (fabric) due to its reliance on a few peak frequencies, thus missing finer texture details. Beta representation had spectral correlations between 0.68 and 0.72, with perceptual similarity from 50% (fabric) to 81% (sandpaper). This method captured the overall spectral envelope but inconsistently altered mid-range frequencies, negatively affecting other textures whose friction signal showed high stationarity, like paper and fabric. The spectral slope had a spectral correlation of 0.7 across textures, with perceptual similarity of 35% (fabric) and 75% (sandpaper). The low similarity is due to its single cutoff frequency suppressing secondary peaks.

In the future, we aim to improve the performance of the Beta representation technique to capture the texture better. Additionally, we plan to include a more diverse set of textures in future work.

References

[1] H. Culbertson, J. Unwin, and K. J. Kuchenbecker, "Modeling and rendering realistic textures from unconstrained tool-surface interactions," *IEEE transactions on haptics*, vol. 7, no. 3, pp. 381–393, 2014.

[2] W. Hassan, A. Abdulali, and S. Jeon, "Authoring new haptic textures based on interpolation of real textures in affective space," *IEEE transactions on industrial electronics*, vol. 67, no. 1, pp. 667–676, 2019.

[3] T. Fielder and Y. Vardar, "A novel texture rendering approach for electrostatic displays," in *International Workshop on Haptic and Audio Interaction Design-HAID2019*, 2019.

[4] J. K. Balasubramanian, D. M. Pool, and Y. Varadar, "Sliding speed influences electrovibration-induced finger friction dynamics in light and moderate touch on touchscreens," *Manuscript yet to be submitted.*