# Perceptually based simple statistic from natural materials for rendering\*

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I. INTRODUCTION

We are extremely good at recognizing which material an object is made of by touch. Haptic perception of materials is based on the dynamic contact between the hand and the material's surface, as we usually slide the hand across the object's surface to understand what material it is made of [1]. During the contact between the skin and the material, the spatial structure of its surface elicits vibrations on the skin. Such temporal signal is the base of haptic material perception [2], [3]. However, it is confounded with the speed at which the material moves relative to the hand, e.g. gratings with different spatial frequency translate to the same temporal frequency when explored at accordingly different speed. Despite this, our perception is speed constant [4], and even passive perception [5].

We previously argued that the relative frequency composition of vibrations elicited by the exploration of natural textures follows a  $\frac{1}{f^s}$  Fourier amplitude spectrum, with s being the slope characterizing this relationship, which is linear in log-log space [6]. We showed that s systematically varies between material categories and correlates with human perceptual judgments. Crucially, such statistics, being a measure of relative spectral composition, is speed invariant [7]. In our experiment participants explored 74 different materials using a pen with a steel tip at 3 different speeds, while we recorded vibrations for 10 s via a mounted accelerometer (ADXL345, 3200 Hz). Afterwards they provided perceptual ratings. As predicted, the vibratory signals for the same material drastically differed across exploration speed (see example in the left panel of Fig.1A), while s was impressively constant (right panel of Fig.1A). Crucially, variation in perceptual ratings across speeds could be explained by variations in s, i.e. speed constancy was higher the less s varied across speeds, indicating that speed constant material perception might be based on s.

Here we tested (1) if speed constancy emerges in a deep neural network trained to classify materials explored at different speeds and (2) if perception of materials can be changed by augmentation with vibrations which change s

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## **II. RESULTS & DISCUSSION**

# A. Speed constant classification of materials relies on s

We trained a recurrent neural network to classify materials based on vibratory signals from explorations at different speeds [7], implicitly training it for speed constancy. The model processes vibratory signals using a bidirectional long short-term memory (BiLSTM) layer, enabling it to analyse temporal dependencies in both forward and backward directions. Each neuron extracts an aggregated representation of the signal, which is then passed through a dense layer that maps it to seven output values (one per material category), used to produce the final classification.



Fig. 1. A. Left: A vibratory signal from the exploration of an example material at slow (red) and fast (green) speed. Right: The average spectral composition across all materials for the slow (red) and fast (green) exploration speed. B. Correlation of neuron activation across speed, as a measure of speed constancy. The first 120 neurons represent the feedforward neurons (yellow), the second 120 the feedback neurons (orange) and the last seven neurons (red) represent the dense layer. Each point represents the correlation for one neuron. The horizontal green line represents the correlation for the s statistics, the blue line for the Fourier Spectrum.

We measured how consistently each neuron responded across speeds by computing Pearson's correlation coefficients for all three speed pairings across materials, then averaged the results. The more speed constant, the higher the correlation. As reference values, we repeated the correlation analysis with *s*, and with the Fourier Spectrum. For the latter, we computed the correlations for the 3 combinations of speed, for each of the bands of the Fourier Spectrum, then averaged.

As expected (Fig.1B), the correlation for s (r = 0.91) was higher than the one for the Fourier Spectrum (r = 0.82). Crucially, the correlations for the feedforward neurons (M = 0.78) were significantly lower than the one for the feedback neurons (t(238) = 12.18, p < 0.0001), lower than for the dense layer neurons (t(125) = 5.46, p < 0.0001) and remarkably close to the one for the Fourier Spectrum. Conversely, the correlation for the feedback neurons (M=0.89) and for the dense layer neurons (M=.95) were very similar to the one for s.

These results suggest that while the feedforward neurons captured low-level properties of the signals and failed to develop a more speed-invariant representation, the feedback and dense layer neurons could do so. Moreover, the representations they captured are as speed-invariant as the s statistics, reinforcing the role of s as a potential solution for speed constancy.

## B. Manipulation of s in augmented materials

To test if changing s in the vibratory signal changes perception, we augmented real materials with vibrations generated by a small haptic actuator (GREWUS, EXA 261808W-01 A, in combination with the sound card of a computer and a custom made amplifier). The actuator was mounted on top of the 3D printed pen with which participants (N=5) explored 3 material samples from the categories fabric, metal and animal. The samples were chosen to be ambiguous based on recordings we have collected previously [7]. The additional vibrations were generated from white noise lowor high-pass filtered using MATLAB functions lowpass and highpass to filter out vibrations above 150Hz and below 250Hz, respectively. In a control condition, no vibration was added during the exploration. Sound was covered by white noise played through noise canceling headphones and ear plugs. Vision of the material and the exploring hand was covered by a curtain. After exploring each material, participants used a slider to indicate how strongly it felt like each material category (e.g. from metal to stone). Each sample was repeated 5 times.

As can be seen in Fig.2 our manipulation of the vibratory signal via augmentation with an additional vibration worked out well. As expected, adding a low vibration made s steeper (red), while adding a high frequency vibration made s shallower (green) as compared to the pure vibration from the exploration (blue). However, contrary to our expectation, average s in the neutral condition deviated from the category prototype only for one of the materials (middle panel), resulting in an initially ambiguous vibratory signal only for one material. Consequently, only for this material there is also ambiguity in the perceptual ratings. Consistent with our hypothesis the manipulation of s affected perception of the material - moving s closer to the category prototype made participants perceive the material less ambiguous. These



Fig. 2. Perceptual ratings as a function of *s* for each material, condition and trial. Augmentation with low frequency is plotted in red, high frequency in green and the control condition (no additional vibration) in blue. Participants are plotted as different symbols and the averages for each condition as crosses. The dotted lines indicate the "typical" (average) slope of the explored material category. The ambiguous neighbor category and the associated direction of slope change is indicated with an arrow.

results are promising, however, larger participant and material samples are required to confirm the causal relationship between s and perception.

Overall, our results suggest that the simple statistic of natural materials, s is a plausible solution for speed-invariant haptic material perception .

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