Natural scenes in tactile texture

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Submitted 20 September 2013; accepted in final form 9 February 2014

OUR SENSE OF TOUCH plays a crucial role in a variety of tasks, from manipulating objects and adjusting grip forces (Johansson and Flanagan 2009; Witney et al. 2004) to exploring the environment (Lederman and Klatzky 1990), for example, when probing the ripeness of a fruit. In even the simplest of tasks, however, the patterns of skin stimulation are complex and difficult to measure. In the laboratory, then, the neural basis of touch is often studied with highly simplified artificial stimuli, which may not be representative of naturally encountered ones. Characterizing cutaneous stimulation patterns encountered in everyday life may thus shed light on the neural basis of touch. While the space of commonly encountered stimuli (i.e., natural scenes) is well characterized for the visual and auditory systems, their somatosensory counterpart is still ill understood.

To fill this gap, we seek to describe the natural scenes of an important component of everyday tactile experience, namely, texture perception, and thereby characterize the stimulation patterns experienced by cutaneous mechanoreceptors during the exploration of textured surfaces. Running a finger over a finely textured surface, such as velvet, produces small complex vibrations in the skin. Our ability to identify velvet and distinguish it from, say, silk relies in part on the transduction and processing of these vibrations (Bensmaia and Hollins 2003, 2005; Hollins et al. 2001, 2002; Hollins and Bensmaia 2007). Indeed, the responses of cutaneous mechanoreceptive afferents, especially rapidly adapting (RA) type I and Pacinian (PC) fibers, have been shown to closely follow texture-elicited vibrations (Weber et al. 2013) and convey texture information. This implies that the skin oscillations themselves ultimately carry information about texture identity. The question remains whether these oscillations are a straightforward product of a texture’s surface profile, as is often implicitly assumed in studies on tactile texture perception.

Here our objective is to systematically analyze the properties of texture-elicited vibrations, determine the extent to which they convey information about surface microgeometry, establish how they are shaped by the geometry of the fingertip skin, and examine the implications of our findings for the neural basis of texture perception.

Previous studies examining texture-elicited vibrations have focused on small sets of (mainly artificial) textures and have used techniques requiring direct skin contact (Bensmaia and Hollins 2003, 2005; Fagiani et al. 2012), which might alter or impede the signal. Furthermore, the factors that shape the vibrations remain unclear. Some studies found that scanning periodic textures elicits vibrations whose frequency is determined by their spatial period (Bensmaia and Hollins 2003; Delhaye et al. 2012; Wiertlewski et al. 2011a). However, experiments using biomimetic fingertips suggest that it is the spatial period of the fingerprints that determines the frequency of the elicited vibrations (Scheibert et al. 2009), although the precise role of fingerprints in texture perception remains controversial (Dahiya and Gori 2010; Fagiani et al. 2012; Fishel and Loeb 2012; Oddo et al. 2011). Here we use a noncontact measurement technique to measure vibrations as they travel across the fingertip skin. We also measure the microgeometry of textures and fingerprints to determine their respective influence on the elicited vibrations.

MATERIALS AND METHODS

Data Collection

Subjects. Nine subjects (5 men, 4 women, 21–37 yr old) were recruited to participate in the vibrometry experiments. All were students or researchers at the University of Chicago. Each subject participated in three experimental sessions, each lasting ~90 min. The vibrometry recordings of one subject were discarded from all subse-

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quent analyses because digitized fingerprints could not be obtained, but visual inspection of the discarded data showed close similarity to the data obtained from the other subjects. All testing procedures were reviewed and approved by the Institutional Review Board for Human Use of the University of Chicago.

Apparatus and stimuli. A rotating drum stimulator was custom designed and built to scan textures across the fingertip (Fig. 1, A and B). This stimulator was a scaled-up version of one that has been described previously (Johnson and Phillips 1988). In brief, textures, mounted on an acrylic cylinder (254 mm in diameter and 305 mm in length), were scanned at a predetermined speed with a rotational motor (SM231DT-PLS2 SmartMotor, Moog Animatics, Santa Clara, CA) equipped with a 100:1 step-down planetary gearhead (23SP100, Carson Manufacturing, Carson City, NV). In one design, the force exerted on the finger was controlled by a motor (SM3416D-PLS2 SmartMotor, Moog Animatics) that drove the drum/rotation motor assembly. The weight of the drum and rotation motor was offset by a mass whose center was distributed symmetrically about the fulcrum where the shaft of the torque motor was located. Because this stimulator required frequent recalibrations, the torque motor was replaced by a vertical stage (PRO115-05MM-150, Aerotech, Pittsburgh, PA) that initiated and terminated contact between the drum and the skin for each texture presentation. With both designs, force was calibrated on a surface-by-surface basis to compensate for the slight effects of texture thickness (see below for force parameters). Finally, the rotating drum assembly was suspended from a 400-mm stage (PRO115-05MM-400, Aerotech) to allow for translations along the length of the drum so that any of the 55 textures could be presented on any given trial. We verified that the drum produces very little vibration, as imposed vibrations have been shown to affect perceived texture (Hollins et al. 2000b).

Texture stimuli, 25 mm wide and 160 mm long, included a variety of everyday fabrics—ranging from relatively coarse (e.g., hucktowel) to fine (microsuede)—and other materials, including leather, suede, foam, vinyl, etc. A small set of sandpapers, gratings, and embossed dot patterns was also included, as such stimuli have been used in a number of previous psychophysical and neurophysiological studies involving texture (Connor et al. 1990; Delhaye et al. 2012; Sinclair and Burton 1991; Sutu et al. 2013; Verrillo et al. 1999; see Table 1 for the full list of textures used in our study). Five textures were fixed around the circumference of the drum to form each of eleven tracks.

Surfaces were scanned across the skin at 40, 80, and 120 mm/s to span the range of scanning speeds observed in natural tactile exploration (Lederman 1983; Morley et al. 1983; Smith et al. 2002). On each trial, the drum began to rotate and was lowered onto the fingertip until the desired force was achieved. Textures were presented for 2.4, 1.2, or 0.8 s at 40, 80, and 120 mm/s, respectively, and the interval between texture presentations was 3.5 s. For sandpapers, gratings, and dot patterns, an indentation (normal) force of 15 g wt was used to prevent skin damage due to the abrasiveness of these textures. The remaining textures were presented at a force of 25 g wt, slightly lower than the average forces deployed during natural tactile exploration (Smith et al. 2002). At these forces, textures were easily perceptible but not uncomfortable for the subjects. The indentation force was calibrated by lowering the drum onto an aluminum block and registering the resulting force with a high-precision scale.

Vibrometry. Laser-Doppler vibrometry, a noncontact measurement technique, was used to record texture-elicited vibrations on the right index fingerpad (Polytec OFV-3001 with OFV 311 sensor head,
Table 1. Textures used in study

<table>
<thead>
<tr>
<th>Texture Description</th>
<th>Material Type</th>
<th>Textile Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Swimwear lining (polyester/spandex)</td>
<td>[J]16</td>
<td></td>
</tr>
<tr>
<td>Sparkle Vinyl Back</td>
<td>[J]31a</td>
<td></td>
</tr>
<tr>
<td>Denim (cotton)</td>
<td>[V]2a</td>
<td></td>
</tr>
<tr>
<td>Corrugated paper</td>
<td>[J]52a</td>
<td></td>
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<tr>
<td>Faux leather (polyester)</td>
<td>[V]17</td>
<td></td>
</tr>
<tr>
<td>Sueded Cuddle</td>
<td>[J]up8</td>
<td></td>
</tr>
<tr>
<td>Drapery tape foam</td>
<td>[J]34</td>
<td></td>
</tr>
<tr>
<td>Sandpaper 320 grit</td>
<td>[P]1</td>
<td></td>
</tr>
<tr>
<td>Grating 3 mm (plastic)</td>
<td>[Y]54a</td>
<td></td>
</tr>
<tr>
<td>Grating 5 mm (plastic)</td>
<td>[Y]36a</td>
<td></td>
</tr>
<tr>
<td>Premier Velvet (polyester)</td>
<td>[J]40</td>
<td></td>
</tr>
<tr>
<td>Suede leather</td>
<td>[J]18</td>
<td></td>
</tr>
<tr>
<td>Stretch denim (cotton/Lycra)</td>
<td>[V]29a</td>
<td></td>
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<td>Crinkled silk</td>
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</tr>
<tr>
<td>Velour (polyester)</td>
<td>[J]21</td>
<td></td>
</tr>
<tr>
<td>Thin corduroy</td>
<td>[V]31a</td>
<td></td>
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<tr>
<td>Silk jacquard</td>
<td>[V]44</td>
<td></td>
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<tr>
<td>Microsuede (polyester)</td>
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<tr>
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<td>[V]2a</td>
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<tr>
<td>Upholstery [T]8</td>
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<td>Stretch velveteen (cotton)</td>
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<td>Wool crepe [V]13</td>
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<tr>
<td>Smooth leather [J]14</td>
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<tr>
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<td>Thick corduroy [T]28a</td>
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<tr>
<td>Hucktowel (cotton)</td>
<td>[J]36a</td>
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<td>Empire Fleece Knit (cotton) [J]11</td>
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<td>Organza [T]31a</td>
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<tr>
<td>Wool/ rayon felt [J]38</td>
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<tr>
<td>Embossed dots 2 mm</td>
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<td>Snowflake Fleece Knit (polyester) [V]25a</td>
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<td>Wool gabardine [V]38</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sandpaper 400 grit [P]5</td>
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</table>

All 55 textures are shown, ordered by perceived roughness from smooth to rough by row and then by column. Asterisks denote periodic textures (see MATERIALS AND METHODS). Letters in square brackets stand for the vendors or manufacturers from whom the texture was purchased: V, Vogue Fabrics Inc., Evanston, IL; T, Textile Discount Outlet, Chicago, IL; J, Jo-Ann Fabric and Craft, Chicago, IL; P, PSI Woodworking Products, Philadelphia, PA; K, Klingspor Abrasives Inc., Hickory, NC; Y, Toyobo Co., Ltd., Osaka, Japan. Superscripted numbers denote the texture order in the clustering analysis shown in Fig. 3.

Polytec, Irvine, CA). The method, described in detail in a previous paper (Manfredi et al. 2012), relies on measuring the velocity of a surface’s movement, in this case the skin, by comparing the internal reference beam to the measurement beam as it is reflected back through the laser aperture (Fig. 1, A and C). The laser was focused on the fingerpad 7–15 mm from the locus of stimulation onto a small square of white-out tape (BIC USA, Shelton, CT) applied to the skin to increase signal strength by increasing reflectivity.

To ensure that the drum touched down in the same place on the finger for each experimental session, an auxiliary positioning laser was used: This second laser was oriented parallel to the length of the drum, skimming the surface of the fingerpad, perpendicular to the finger’s axis to mark the center of contact between drum and fingerpad. The hand was comfortably restrained in a custom-made hand holder and arm rest, with the index finger elevated by 40° above horizontal to maximize contact between the rotating drum and the fingerpad. A small drop of cyanoacrylate was used to glue the fingernail to the holder to ensure comfort and minimize finger movement during the recordings.

Each texture was presented 10 times at each speed, with experiments distributed over 3 experimental sessions. Vibrometry data were digitized at 100 kHz. A window of 500 ms was taken from the full traces, irrespective of their total duration, which varied depending on the scanning speed. To transform the data to vibrations experienced at the locus of stimulation, the recorded vibrations were corrected in a frequency-dependent manner based on the previously measured rate at which vibrations decay as they travel away from the locus of stimulation (Manfredi et al. 2012). Recorded velocities were numerically integrated by the trapezoidal method to yield skin displacements. Power spectral densities were then calculated from the skin displacements.

Fingerprint digitization. Fingerprints from the right index finger of each subject were obtained with a SecuGen Hamster IV fingerprint scanner (SecuGen, Santa Clara, CA) yielding 508 DPI grayscale images. While we scanned the entire fingertip, in all analyses reported here we only used images of the tip of the finger, i.e., the part that was in contact with the drum during the vibrometry measurements. Scanned images were up-sampled to ×10 resolution with cubic spline interpolation and then converted into binary images by setting a threshold. Next, all visible structures (corresponding to fingerprint ridges) were shrunk to single pixel width, using the “thin” option of the bwmorph function in the MATLAB Image Processing Toolbox (The MathWorks, Natick, MA). A distribution of distances between epidermal ridges along the scanning direction could now easily be obtained. We restricted this distribution to a range of 0.3–0.9 mm to exclude artifacts and took the mean of the resulting distribution as our measure of the subject’s epidermal ridge distance. Our algorithm is
similar to other approaches for calculating epidermal ridge distance (see Maltoni et al. 2009 for an overview). We only measured the distance of ridges along the scanning direction, since it is along this axis that the ridges interact with the surface.

Psychophysics. Eight subjects (6 men, 2 women, 18–31 yr old) provided informed consent and participated in this study. On each trial, the subject was presented with 1 of 55 textures and produced a rating in proportion to its perceived roughness, where a rating of 0 denoted a perfectly smooth surface. Each texture was presented once in each of six experimental blocks; ratings were normalized by the mean of each block and averaged, first within and then across subjects. Ratings of roughness were highly consistent across subjects (intersubject correlation: 0.91 ± 0.03, mean ± SD). All procedures were approved by the Institutional Review Board of the University of Chicago.

Data Analysis

Texture classification. To determine whether the vibrations generated by one surface can be distinguished from those generated by another, we attempted to classify textures on the basis of the vibrations they elicited in the skin. A classifier was run for each subject and for each of the three scanning speeds. Specifically, we performed a bootstrap analysis such that, on each iteration, we randomly split the power spectra obtained from all trials for any given texture into two groups, A and B, and averaged the spectra across trials within each group. We then computed the distance (using 1 of 3 metrics; see below) between the spectra of each texture in group A and those of all the textures in group B (yielding \(55 \times 55 = 3,025\) distances for each A/B texture pair). We then ascribed each (group A) texture to the texture class that yielded the lowest distance. We repeated this process 100 times and computed the classification accuracy by determining the proportion of correctly classified textures.

We used three different distance measures to examine the contribution of different aspects of the power spectra to classification performance. First, to gauge how well textures could be discriminated on the basis of the amplitude of the elicited vibrations alone, we summed the power spectra over frequencies and set the distance as the absolute difference between the summed power spectra. Second, to assess the influence of frequency composition (independent of vibratory amplitude) on discrimination accuracy, we normalized each power spectrum to sum to unity. We then used multiple discriminant analysis (MDA; see Duda et al. 2001 for more background; see Hipp et al. 2006 for an application to the discrimination of whisker vibrations) to project the power spectra into a lower-dimensional space (3D) that was maximally discriminative across textures and calculated the Euclidean distance in this space. This method ensured that each frequency component was weighted according to its discriminatory power. Third, to examine the contribution of both amplitude and frequency, we added another bin to the normalized frequency spectra containing the summed power and then performed MDA on this extended representation as described above.

For grouping textures on the basis of their pairwise distances, we used MATLAB’s hierarchical clustering functions. First, we built an agglomerative hierarchical cluster tree, using the \(\text{linkage}\) function. We used the distances computed at 120 mm/s using the normalized power spectra, as these resulted in high classification accuracy. However, the resulting clusters were similar at all speeds. Next, we generated dendrograms from the cluster tree that ordered the textures according to the identified cluster distances. We used this ordering to rearrange the distance matrix for visualization (see Table 1 for the final order).

\[
f_t = v/p_s \tag{1}\]

where \(f_t\) is the temporal frequency in hertz, \(v\) is the scanning speed in millimeters per second, and \(p_s\) is the spatial period in millimeters. In the following, we use either representation, depending on what is most intuitive given the context.

Characterizing the periodicity of textures. To split textures into a periodic and a nonperiodic set, we devised a simple criterion of periodicity. The profilometric frequency spectrum of nonperiodic textures, such as sandpaper, is well characterized by a power law. Furthermore, for our textures, any significant deviation from a straight line in log-log coordinates generally indicates periodicity, since the surface profiles of the periodic textures in our set are generally close to sinusoidal. With this in mind, we subtracted a straight line fit from the log-log power spectra of each texture and then thresholded the transformed power spectra: Any texture crossing the threshold (set to 10 dB) was classified as periodic. With this method, periodic structure was easy to detect and the measure was insensitive to changes in the threshold criterion (over a range from 7.5 to 15 dB). See Table 1 for all periodic textures. Note that, when comparing spectral peaks between periodic and nonperiodic textures, we only included textures in the periodic set if the frequency of the spectral peak was higher than the lower-frequency cutoff for the vibrometry.

Estimation of the fingertip filter. Sliding the fingertip over a textured surface transforms the surface profile into oscillations that travel along the fingertip skin. This transformation can be approximated by a simple linear filter. In the frequency domain, this filter can be estimated by dividing the vibrometric power spectra by the corresponding profilometric power spectra. The resulting filter indicates which frequencies of the stimulus are boosted or suppressed in its interactions with the fingertip.

Determining the effect of scanning speed on the elicited vibrations. To test how well the frequency composition of the recorded skin vibrations scales with scanning speed, we computed the correlation between the power spectrum at speed \(v\) shifted along the frequency axis by a multiplicative factor \(\alpha\) and the power spectrum at speed \(\alpha v\) (\(r_{\text{trans}}\)). We also computed the correlation between the two spectra without shifting the power spectrum obtained at speed \(\alpha v\) (\(r_{\text{no-trans}}\)). For example, to calculate \(r_{\text{trans}}\), the bin frequencies of power spectra obtained at 80 mm/s were multiplied by 1.5 and compared (via correlation) to the power spectrum at 120 mm/s, and to calculate \(r_{\text{no-trans}}\) we computed the correlation between the untransformed spectra obtained at 80 mm/s and those obtained at 120 mm/s. To the extent that the spectrum shifts follow the relationship shown in Eq. 1, \(r_{\text{trans}}\) should be higher than \(r_{\text{no-trans}}\). The degree to which a texture translated was then given by

\[
I_{\text{trans}} = \tanh\left(\frac{(\tan^{-1}(r_{\text{trans}}) - \tan^{-1}(r_{\text{no-trans}}))}{2}\right) \tag{2}\]

where \(r_{\text{trans}}\) takes on a value of +1 if \(r_{\text{trans}} \gg r_{\text{no-trans}}\) and −1 if \(r_{\text{no-trans}} \gg r_{\text{trans}}\).

RESULTS

We scanned 55 different textures at 3 different speeds across subjects’ fingertip skin with a custom-made rotating drum stimulator and measured the vibrations elicited in the skin with a laser-Doppler vibrometer (Fig. 1, \(A–C\)). The textures included mainly everyday materials, such as fabrics, as well as some artificial stimuli, such as embossed dot patterns and gratings (see Table 1 for full list). Inspection of the measured vibrations revealed that different textures elicited vibrations that differed in amplitude, periodicity, and frequency composition (Fig. 1D). Vibrations ranged from highly periodic (velvet) to highly nonperiodic (fleece), with many textures comprising both periodic and nonperiodic components (drapery tape).
Texture Classification Based on Vibrations

To carry texture information, skin vibrations must vary across textures yet be consistent across different presentations of the same texture. To test whether individual textures could be distinguished on the basis of the vibrations they elicit in the fingertip skin, we implemented a classification algorithm (see MATERIALS AND METHODS) that discriminates textures on the basis of features extracted from the recorded skin oscillations at a given speed. We found that textures were poorly classified on the basis of the amplitude of the elicited vibrations alone (Fig. 2). The low informativeness of vibratory amplitude can be partly attributed to the fact that amplitude could vary considerably between repeated presentations of the same texture, despite the precise movements of the texture drum. Mechanical properties of the fingertip, such as hysteresis and changes in stiffness over the course of the experiment (Nakazawa et al. 2000; Pawluk and Howe 1999; Serina et al. 1997; Wang and Hayward 2007), along with variations in contact lubrication (Andre et al. 2010) are likely to be responsible for these trial-to-trial variations in the intensity of texture-elicited vibrations.

In contrast to vibratory amplitude, the frequency composition of the elicited vibrations (characterized with normalized power spectra) was highly informative as to texture identity, with classification accuracy reaching 93% at 120 mm/s (Fig. 2). Classification of textures using both amplitude and frequency composition led to a negligible increment in performance. We further observed that classification performance improved slightly with increased speed, probably because of higher vibratory power and thus higher signal-to-noise ratio at those speeds. Furthermore, the distance matrix exhibited some interpretable structure (Fig. 3): For example, sandpapers and fuzzy textures formed distinct clusters, and textures with complex spectral shapes were highly dissimilar from all other textures.

Results from our classification analysis suggest, then, that there is sufficient information in texture-elicited vibrations, specifically in their frequency composition, to mediate our ability to identify and discriminate textures.

Relationship Between Texture-Elicited Vibrations and Surface Microgeometry

Having established that individual textures can be classified on the basis of the skin vibrations they elicit, we next deter-

Fig. 2. Classification accuracy over all textures using either the amplitude of the elicited vibrations (open bars), the normalized frequency spectrum (filled bars), or both (gray bars) as a basis for classification. Results are shown for all 3 scanning speeds. Error bars denote the SE across subjects. Chance performance is ~0.018 (as there are 55 textures in our set). While textures can easily be classified on the basis of the frequency composition of the vibrations they elicit, the amplitude of the vibrations alone is only marginally informative about texture identity.

Fig. 3. Distance matrix for all textures, scanned at 120 mm/s, based on vibratory spectra (distances shown on logarithmic scale). Textures are ordered such that those that yield similar spectra are close together (see MATERIALS AND METHODS and see Table 1 for full ordering). The white boxes highlight 4 texture sets, with examples from these sets shown to either side of the distance matrix. For each example, the image on left shows a small patch of the texture’s surface profile (5 × 5 mm), while the graph on right shows the power spectral density of the elicited vibrations at 120 mm/s (orange) and that of the corresponding surface profile (black). Of the four highlighted sets, set 1 includes the sandpapers; set 2 fuzzy, hairy textures; set 3 two coarse textures of similar spatial period; and set 4 textures that are dissimilar from all other textures, most of which yield complex vibrational power spectra.
mined the extent to which vibratory spectra followed predictably from texture microgeometry and scanning speed. In other words, to what extent does the stimulation pattern experienced by receptors embedded in the skin approximate the spatial structure of the surface? To address this question, we measured the three-dimensional microgeometry of the surfaces with a laser microscope and compared the frequency composition of each surface profile along the scanning direction with that of the elicited vibrations, scaling the profilometric spectra to account for scanning speed (see MATERIALS AND METHODS).

First, we asked whether the amplitude of the elicited skin vibrations could be predicted from the amplitude of the profilometric spectra (from which the average height of textural features can be estimated). We found that the correlation between profilometric and vibrometric amplitude (assessed by summing the respective power spectra) was close to 0 ($r = 0.07$ for 40 mm/s, $r = 0.08$ for 80 mm/s, $r = 0.09$ for 120 mm/s). In other words, the strength of the elicited vibrations on the skin could not be straightforwardly predicted from the textures’ surface profiles. This failure is perhaps not surprising given the complex biomechanical interactions that take place between the textured surface and the fingertip skin during scanning. For example, soft materials will be distorted more when touched than hard materials, a phenomenon that is not reflected in the profilometry. Indeed, as our set of textures mainly comprises everyday textures, many of them include complex and compliant surface features.

Next, we examined how well the frequency composition of the elicited vibrations matched the frequency composition of the textures’ surface profiles. We could not simply compute the correlation between matched profilometric and vibrometric spectra as the latter were all characterized by a decrease in power with frequency (Wiertlewski et al. 2011a), which then dominated the correlation values. Instead, we split the textures into a periodic and a nonperiodic set, depending on whether the surface profile exhibited a dominant peak in the power spectrum (see examples in Fig. 4 and the full set in Table 1).

Periodic textures (Fig. 4, A and B) typically evoked dominant peaks in the vibrometric spectra that matched their spatial period as measured by profilometry (Fig. 5A). The peaks in both spectra shifted depending on the scanning speed. The majority of the misaligned peaks in the vibratory spectra fell

![Fig. 4](image)

**Fig. 4.** A: profilometry for 3 periodic textures. The white arrow indicates the scanning direction. Patches are $5 \times 5$ mm in size. B: power spectral densities (PSDs; shown on linear scale) for the textures shown in A as calculated from profilometry (black lines, adjusted for scanning speed) or vibrometry (blue and orange lines) at speeds of 80 and 120 mm/s (left and right, respectively) averaged across all subjects. The frequency composition of the elicited vibrations matches the frequency content of the periodic textures to some extent. C: profilometry for 3 nonperiodic textures. D: PSDs calculated from profilometry (black lines) and vibrometry (blue and orange lines) for 2 speeds averaged across subjects (same as in B). While the spectral power in the textures’ surface profiles decreases with frequency, the power spectra of the recorded vibrations exhibit spectral peaks just below 200 Hz and around 250 Hz at scanning speeds of 80 and 120 mm/s, respectively.

![Fig. 5](image)

**Fig. 5.** A: peak frequency in the surface profile vs. peak frequency in the vibrations for all periodic textures at the 3 different speeds. Periodic textures often elicit spectral peaks at the frequency determined by their dominant spatial period. B: profilometric spectral centroids against vibrometric spectral centroids for all nonperiodic textures at a scanning speed of 80 mm/s. The frequency composition of the textures’ surface profiles is reflected in that of the skin vibrations, but the range over which the vibrometric centroids vary is much smaller.
around 250 Hz at a speed of 120 mm/s and just below 200 Hz at a speed of 80 mm/s (we investigate these peaks below). Nonperiodic textures did not exhibit dominant peaks in their profilometric power spectra (Fig. 4, C and D). Instead, power declined with frequency at rates that varied across textures. Vibrometric spectra evoked by these surfaces exhibited peaks around 250 Hz at 120 mm/s and just below 200 Hz at a speed of 80 mm/s that had no counterparts in the corresponding profilometric spectra. Power above 400 Hz was minimal in the vibrometric spectra but not in the profilometric spectra. To test the relationship between the vibrations elicited by nonperiodic textures and the profile of the textures, we calculated the spectral centroids of the profilometric power spectra and compared them with the spectral centroids of the vibratory power spectra for all nonperiodic textures. We found that profilometric centroids were highly correlated with the vibrometric centroids at all three speeds (Fig. 5B; \( r = 0.72 \) at 40 and 80 mm/s and \( r = 0.77 \) at 120 mm/s). Thus the frequency composition of skin vibrations captures some aspects of surface structure, for both periodic and nonperiodic textures, explaining why even nonperiodic textures are easily discriminable on the basis of skin oscillations alone (as shown above). The resulting vibrations are not shaped by surface profile alone, however: Skin vibrations tend to exhibit frequency peaks between 150 and 250 Hz that do not match any peaks in the surface microstructure (see Fig. 4D), and the spectral centroids of the vibrations tend to cluster around those frequencies, rather than spanning the broader range of the profilometric centroids (Fig. 5B).

Thus surface microgeometry is reflected to some extent in the elicited skin vibrations, but the match between surface and vibrations is imperfect, suggesting that vibrations may be shaped in part by the biomechanical properties of the skin.

Effect of Scanning Speed on Texture-Elicited Vibrations

As expected, the peak frequencies of the vibrations elicited by periodic textures shifted systematically toward higher frequencies with increases in scanning speed. While this effect has been described previously for periodic textures, it is not straightforward to quantify how the frequency spectra of texture vibrations translate as a function of scanning speed, we developed an index (Eq. 2) that takes on a value of +1 if the spectrum scales perfectly and a value of −1 if the spectrum does not change across scanning speeds. We found that periodic textures scored 0.66 ± 0.16 (mean ± SD, averaged across speeds) on this measure and nonperiodic textures (e.g., sandpapers, fuzzy fabrics) yielded nearly identical values [0.67 ± 0.19; 2-sample t-test: \( P = 0.86 \), \( t(53) = 0.17 \)]. We conclude that texture-elicited skin vibrations scale systematically with scanning speed, whether or not textures are periodic.

A Role of Fingerprints in Shaping Texture-Elicited Vibrations?

Having established that texture-elicited vibrations do not straightforwardly reflect the surface microgeometry, we investigated other factors that might shape these vibrations. One possibility is that fingerprint microgeometry plays a role (cf. Scheibert et al. 2009). To test this possibility, we measured the spatial period of the subjects’ fingerprints based on digitized scans (see MATERIALS AND METHODS) and estimated the frequency of the vibrations that would be produced given the spatial period at each scanning speed (cf. Eq. 1). We found that the power spectra of the recorded vibrations averaged over all textures exhibited spectral peaks at frequencies that corresponded to the average fingerprint spatial periods (Fig. 6A). The transformation from the profilometric to the vibrometric spectra can be approximated as a linear filter (see MATERIALS AND METHODS). We found that the estimated filters boosted spatial periods that were close to the average spatial period of the fingerprints (Fig. 6B). The influence of fingerprints can therefore explain the presence of spectral peaks in the vibratory spectra that do not match peaks in their profilometric counterparts (as described above; see Fig. 4D and Fig. 5).

To verify that the elicited frequencies were in fact dependent on the fingerprint microgeometry of individual subjects, we examined whether the frequency composition of subject-specific filters covaried with that subject’s fingerprint period. Indeed, we found that subjects with coarser fingerprints exhibited filters with peaks at lower frequencies than subjects with

![Image](https://example.com/image.png)

Fig. 6. A: average PSDs over all textures for profilometry (dark) and vibrometry (colored) at the 3 different speeds. Arrows denote average fingerprint spatial period across all subjects at the 3 speeds. As can be seen, vibrations exhibit peaks that match the average fingerprint spatial period. B: linear filters of the transformation from profilometric to vibrometric spectra (see MATERIALS AND METHODS) converted from frequency to spatial period at 80 and 120 mm/s averaged over subjects (PSDs obtained at 40 mm/s were eliminated from this analysis as they abutted the lower frequency limit). The arrow denotes the average ridge distance of the fingerprints across subjects. The filters consistently reach peak power close to the spatial period of the fingerprints. C: left: average filters at 80 mm/s for each of 2 subjects with different fingerprint spatial periods. Right: fingerprints for each subject. The filters exhibit peaks at the frequency corresponding to the spatial period of the fingerprint. D: peak spatial period for each filter (across all textures at 80 mm/s) vs. average fingerprint ridge distance for the corresponding subject. The dotted line denotes unity. As expected, denser fingerprints lead to higher peak frequencies.
finer fingerprints, and that the observed filter peak spatial periods closely aligned with the values expected given each subject’s fingerprint period (Fig. 6, C and D). It should be noted that different scanning directions, for example, transverse rather than longitudinal swiping, should influence the elicited frequencies insofar as fingerprint ridges are differently oriented with respect to the texture (Prevost et al. 2009).

**Relationship Between Texture Vibrations and Perception**

Perceived roughness has previously been found to increase with the logarithm of vibratory power (Bensmaia and Hollins 2003, 2005; Yoshioka et al. 2007). We replicated this result with our present measurements, finding that 83% of the variance in roughness judgments could be accounted for by the logarithm of power. Thus, while vibratory power conveys relatively little information about texture identity, it is strongly related to perceived roughness. Interestingly, there was no relationship between roughness judgments and the log spectral power of the profile ($r = −0.05$), further bolstering the claim that the skin response is not a straightforward reflection of the surface microgeometry. As might be expected, afferent responses are even better predictors of perceived roughness—accounting for 95% of the variance—than is vibratory power (cf. Weber et al. 2013). Indeed, each afferent class conveys a signal that is a nonlinear transformation of the spatio-temporal pattern of skin deformation (Dong et al. 2013; Kim et al. 2010; Sripati et al. 2006), and it is those signals that are processed centrally to culminate in perception.

**DISCUSSION**

During natural tactile exploration complex high-frequency vibrations are elicited in the fingertip skin, and these vibrations carry information about the surface texture of the manipulated object. In this study, we used a noncontact measurement technique to record the skin vibrations elicited by a range of everyday textures. We found that the frequency composition of texture-elicited vibrations is highly informative about texture identity and supports texture discrimination with high accuracy. Furthermore, the elicited vibrations reflect not only the surface profile but also the fingerprint microgeometry, and change systematically with scanning speed. Thus skin oscillations are shaped both by the individual textures and by properties of the skin. Achieving a complete understanding of texture perception will require consideration of both textural properties as well as the physical characteristics of the fingertip skin, such as its stiffness, fingerprint geometry, and mechanoreceptor distribution.

**Implications for Texture Perception**

Our results suggest that the frequency composition and the amplitude of texture-elicited vibrations carry different aspects of textural information. Indeed, vibratory power was found to be highly correlated with perceived roughness, and textures that were misclassified on the basis of power were of similar roughness. However, roughness is only one perceptual dimension along which textures may vary (Hollins et al. 2000a), and our classification analysis shows that vibratory amplitude alone is not sufficient to establish texture identity (as many of the textures in our set were relatively fine and similar in vibratory power and thus roughness). While the relationship between roughness and vibratory power has been previously established, our results show that the vibratory frequency spectrum provides information above and beyond surface roughness and could provide a signal for establishing texture identity. For example, the vibratory spectra of the sandpapers formed a tight cluster despite the fact that they varied widely in perceived roughness.

In our classification analysis, we made no attempt to describe the distances between textures in a biologically plausible way. For example, highly periodic textures were found to be highly discriminable on the basis of their vibratory spectra. However, while some information about frequency is perceptually available, our ability to distinguish different vibratory frequencies is relatively crude, with discrimination thresholds on the order of 20% (Mountcastle et al. 1969; Rothenberg et al. 1977). In fact, the discriminability of complex vibrations can be well approximated by a model that takes into account the frequency dependence of our tactile sensitivity (Bensmaia et al. 2005). Such a model also predicts the discriminability of textures on the basis of the spectra of the vibrations they elicit in the skin (Bensmaia and Hollins 2005).

**Implications for Neural Mechanisms**

While the importance of skin vibrations in texture perception is beginning to gain traction, the implications for neural coding remain to be elucidated. Until now, studies examining the neural basis of texture have focused almost exclusively on the coding of roughness of coarse gratings or Braille-like dot patterns (Blake et al. 1997; Connor et al. 1990; Connor and Johnson 1992), concluding that slowly adapting type I (SA1) and RA fibers, which densely innervate the fingertip skin, convey a spatial “image” of a textured surface as it slides across the fingertip. However, most of the textures in our set, and indeed most natural textures, comprise textural features too fine to be resolvable by a spatial mechanism, given the innervation density of the skin and receptive field sizes on the fingertip (Johansson and Vallbo 1979). Additionally, SA1 afferents produce a weak and uninformative response to most natural textures (Weber et al. 2013). Instead, texture information is conveyed by skin oscillations that are encoded in the neural responses of RA and PC afferents. These fibers are highly sensitive to skin vibrations and convey signals that are highly informative about texture identity (Weber et al. 2013). In fact, skin oscillations are more closely associated with the neural responses than is the surface microgeometry of the textures.

To the extent that texture perception relies on the transduction and processing of complex, high-frequency vibrations, we can examine how these are encoded in the peripheral and central nervous systems to understand the neural basis of texture perception. At the somatosensory periphery, the intensity of skin vibrations is encoded in the strength of the response of populations of mechanoreceptive afferents (Muniak et al. 2007), while their frequency composition is encoded in millisecond-precision temporal patterning in afferent responses (Mackevicius et al. 2012; Mountcastle et al. 1972). Similarly, the amplitude and frequency composition of high-frequency skin oscillations are represented by rate and timing codes, respectively, in primary somatosensory cortex (Harvey et al. 2013). Texture scanning thus produces oscillations in the skin.
whose envelope and frequency composition are reflected in the neural response, both at the periphery and in cortex. According to our classification analysis, the frequency composition of texture-elicited vibrations is considerably more informative than their amplitude. Given its role in encoding vibratory frequency in the nerve, we would thus expect spike timing to convey information about texture identity, a prediction that is borne out in the analysis of afferent responses (Weber et al. 2013).

The firing rates of primary somatosensory cortical neurons to gratings and Braille-like dot patterns have been shown to be related to the perceived roughness of these stimuli (Chapman et al. 2002). This result is compatible with the finding that vibratory amplitude is encoded in cortical firing rates (Harvey et al. 2013) and strongly related to perceived roughness (Bensaoua and Hollins 2003, 2005). While this interpretation is appealing, the perceived roughness of textured surface seems to be determined not just by a vibratory mechanism, on which the present study focuses, but also by a spatial one, which dominates for dot patterns and gratings (Connor et al. 1990; Weber et al. 2013). Better disentangling of the underpinnings of the cortical representation of texture will require that a more diverse set of textures be used to explore them.

In this study, we have only considered the strength and frequency composition of skin vibrations close to the location of contact with the texture on the fingertip. However, high-frequency skin vibrations elicited at the fingertip propagate the full length of the finger (Manfredi et al. 2012) and have been recorded as far away as the wrist (Delhaye et al. 2012). Skin vibrations also decay in a frequency-dependent manner, a mechanism that, at least on the fingerprint, amplifies frequencies in the PC response range (Manfredi et al. 2012). Given the exquisite sensitivity of PC fibers to high-frequency vibrations (with thresholds below 1 μm around 250 Hz), texture-elicited vibrations should excite PC fibers across the entire thumb; for example, simply making contact with objects during grasping has been shown to excite PC fibers on the palm and wrist (Westling and Johansson 1987). Furthermore, while the innervation density of SA1 and RA afferents is highest on the fingertip and declines as one proceeds proximally, this decline is much less pronounced for PC fibers (Vallbo and Johansson 1984). Thus most responding PC fibers are located outside of the contact area (Manfredi et al. 2012). As a result, roughness discrimination thresholds are unimpaired even when tactile responses from the finger are blocked, suggesting that neural responses from remote sites can drive perceptual judgments (Libouton et al. 2012).

**Skin Oscillations and Scanning Speed**

The tactile perception of texture is relatively insensitive to changes in scanning speed (Lederman 1983), which is surprising given that scanning speed exerts a powerful influence on texture-elicited vibrations and on afferent responses to texture (Weber et al. 2013). However, textures can easily be discriminated on the basis of the oscillations they produce in the skin at a given speed, and speed has a systematic effect on these oscillations. Thus to accurately discriminate between different textures during natural exploratory movements, which generally exhibit sinusoidal speed profiles (Morley et al. 1983), texture-related signals must be interpreted in the context of the scanning speed in which they occur. Information about scanning speed is perceptually available, as evidenced by the fact that humans can accurately scale tactile speed, even in the absence of active movement (Depeault et al. 2008). This speed signal might then be combined with texture information carried by skin oscillations during surface exploration to yield a speed-invariant texture percept. Alternatively, it is also possible that, rather than being dependent on the absolute frequency of texture-elicited vibrations, texture perception relies on a specific harmonic structure in these vibrations, analogously to timbre perception in the auditory system (Yau et al. 2009). Such a scheme would not necessarily require a precise speed signal. To our knowledge, no work has been reported that would rule out one of these possibilities.

**Role of Fingerprints in Texture Perception**

The role of fingerprints in tactile perception has been controversial. While they were originally thought to enhance spatial discrimination as mediated by SA1 afferents (Cauna 1954; Maeno et al. 1998), more recent studies have cast doubt on this hypothesis (Gerling and Thomas 2008). Studies with biomimetic devices have led to the proposition that the spatial period of fingerprints would be reflected in the frequency spectrum of vibrations elicited by nonperiodic textures (Scheibert et al. 2009). However, other studies have suggested that fingerprints merely enhance the magnitude of the elicited vibrations indiscriminately (Oddo et al. 2011) or that their frequency composition depends on the ratio between the spatial period of the texture and that of the fingerprints (Fagioli et al. 2011, 2012).

We found that our set of everyday textures elicited vibrations that contained frequencies corresponding to a subject’s fingerprint geometry. Crucially, this was the case not only for nonperiodic textures (like sandpaper) but also for most textures in our set, which spanned the range from nonperiodic to periodic and were made from a variety of different materials.

The fact that skin vibrations tend to peak in frequency at a value determined by the spatial period of the fingerprints and scanning speed implies a texture-invariant signal that could be exploited for accurate determination of scanning speed (Wandersman et al. 2011). Information about scanning speed is perceptually available during passive motion (Depeault et al. 2008) and could be used to support texture constancy (Lederman 1983).

Intriguingly, different fingerprint layouts affect the frequency composition of texture-elicited vibrations differently. One possibility is that fingerprints enhance textural features at a spatial scale similar to that of the fingerprints themselves, whose spatial scale is smaller than that of the innervation density of the skin (~0.5 mm vs. ~1 mm). Given the well-documented variation in fingerprint layout over the human population (Acree 1999; Cummins et al. 1941; Ohler and Cummins 1942), our results further raise the possibility that fingerprint geometry might affect perceptual capabilities in texture perception, as does finger size in fine spatial discrimination (Peters et al. 2009).

It should be noted that other skin properties, such as skin thickness and stiffness, have also been shown to affect the tactile perception of texture (Lederman 1976) and probably contribute to shaping texture-elicited vibrations. For example,
the rate of decay of skin vibrations varies widely across subjects (Manfredi et al. 2012), a variability that reflects differences in skin properties. Furthermore, other properties of the surfaces themselves, such as surface adhesion, compliance, and friction (which were not measured in the present study) likely also shape the skin vibrations (see, e.g., Smith 1994).

Comparison to Findings in the Rodent Whisker System

Our results straightforwardly invite comparisons to the rodent whisker system. Textured surfaces elicit small, high-frequency vibrations in individual whiskers during active texture exploration. These vibrations depend on textural features (Ritt et al. 2008) but are also shaped by the biomechanical properties of the whiskers themselves (Bagdasarian et al. 2013; Hartmann et al. 2003), which amplify some frequencies and suppress others. Furthermore, whisker movements are informative enough to support texture classification (Hipp et al. 2006). Thus vibrational cues play an important role in both human and rodent texture perception, which strengthens the proposition that similar neural codes might underlie texture perception at the somatosensory periphery of rodents and primates (see also Diamond 2010). Indeed, similar to their primate counterparts, peripheral afferents in the rodent whisker system respond to high-frequency whisker oscillations with precisely timed action potentials (Arabzadeh et al. 2005; Jones et al. 2004), and part of this temporal structure is preserved in barrel cortex (Ewert et al. 2008).

Applications

In addition to their implications for neural coding and texture perception, the present results may have practical applications. Our methods to measure and analyze texture-elicited vibrations will help guide attempts to render virtual textures (e.g., Chubb et al. 2010; Romano and Kuchenbecker 2012; Wiertlewski et al. 2011b). Furthermore, our results suggest that the biomechanical properties of the skin and the geometry of individual fingerprints, rather than texture properties alone, need to be taken into account when attempting to replicate textures that feel natural. Finally, understanding the role of vibrations in texture perception will inform the development of sensorized artificial fingers (e.g., Fishel and Loeb 2012; Oddo et al. 2011) for use in biomimetic neuroprostheses.

ACKNOWLEDGMENTS

The authors thank Angela Sherman and Oksana Lasowsky for their assistance in data collection and Justin Lieber for comments on a previous version of this article.

GRANTS

This work was supported by National Science Foundation Grant IOS-1150209.

DISCLOSURES

No conflicts of interest, financial or otherwise, are declared by the author(s).

AUTHOR CONTRIBUTIONS

Author contributions: L.R.M., M.C.Z., and V.S.P. performed experiments; H.P.S. and S.J.B. approved final version of manuscript; H.P.S., J.F.D., V.S.P., and S.J.B. conception and design of research; H.P.S. analyzed data; H.P.S. and S.J.B. interpreted results of experiments; H.P.S. prepared figures; H.P.S. and S.J.B. drafted manuscript; H.P.S. and S.J.B. edited and revised manuscript.

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J Neurophysiol • doi:10.1152/jn.00680.2013 • www.jn.org