Natural scenes in tactile texture


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Abstract

Sensory systems are designed to extract behaviorally relevant information from the environment. In seeking to understand a sensory system, it is important to understand the environment within which it operates. In the present study, we seek to characterize the natural scenes of tactile texture perception. During tactile exploration, complex high-frequency vibrations are elicited in the fingertip skin, and these vibrations are thought to carry information about the surface texture of manipulated objects. How these texture-elicited vibrations depend on surface microgeometry and on the biomechanical properties of the fingertip skin itself remains to be elucidated. Here, we record skin vibrations, using a laser Doppler vibrometer, as various textured surfaces are scanned across the finger. We find that the frequency composition of elicited vibrations is texture-specific and highly repeatable. In fact, textures can be classified with high accuracy based on the vibrations they elicit in the skin. As might be expected, some aspects of surface microgeometry are directly reflected in the skin vibrations. However, texture vibrations are also determined in part by fingerprint geometry. This mechanism enhances textural features that are too small to be resolved spatially, given the limited spatial resolution of the neural signal. We conclude that it is impossible to understand the neural basis of texture perception without first characterizing the skin vibrations that drive neural responses, given the complex dependence of skin vibrations on both surface microgeometry and fingertip biomechanics.

Key words: texture perception, skin oscillations, somatosensory periphery

Introduction

Our sense of touch plays a crucial role in a variety of tasks, from manipulating objects and adjusting grip forces (Witney et al. 2004; Johansson and Flanagan 2009) 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 using 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 (Hollins et al. 2001; Hollins et al. 2002; Bensmaia and Hollins 2003; Bensmaia and Hollins
2005; Hollins and Bensmaia 2007). Indeed, the responses of cutaneous mechanoreceptive afferents,
especially rapidly adapting type I (RA) 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; Bensmaia and Hollins 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; Wiertlewski et al. 2011a; Delhaye et al. 2012). But 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), though the precise role of fingerprints in texture perception remains controversial (Dahiya and Gori 2010; Oddo et al. 2011; Fagiani et al. 2012; Fishel and Loeb 2012). Here, we use a non-contact 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 males, 4 females, 21-37 years 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 around 90 minutes. The vibrometry recordings of one subject were discarded from all subsequent 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 performed in compliance with the policies and procedures of 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 (Figure 1A,B). This stimulator was a scaled-up version of one that has been previously described (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 using a rotational motor (SM2316DT-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, Santa Clara, CA) 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, Inc., 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, Inc., Pittsburgh, PA) 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 vibrations 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 (hucktowel, e.g.) 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; Sinclair and Burton 1991; Verrillo et al. 1999; Delhaye et al. 2012;
Sutu et al. 2013; 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 using a high-precision scale.

Vibrometry: Laser Doppler vibrometry, a non contact measurement technique, was used to record texture-elicited vibrations on the right index fingerpad (Polytec OFV-3001 with OFV 311 sensor head, Polytec, Inc., 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 (Figure 1A,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, Inc., 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 ten times at each speed, with experiments distributed over three 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 using the trapezoidal method to yield skin displacements. Power spectral densities were then calculated from the skin displacements using Welch's method, which reliably estimates power spectra even from noisy recordings. Unless otherwise noted, frequency components below 50 Hz are ignored due to recording noise at such low frequencies.

3D laser measuring microscope: The three dimensional surface profile of the texture samples were recorded using an Olympus LEXT OLS4000 Laser Microscope (Olympus Corp., Hamburg, Germany). A 30 mm x 30 mm piece of each texture was cut and affixed to a flat substrate on the measurement stage. The textures were fixed to the substrate with double-sided tape along its two opposite edges. One side of the sample was adhered first, with light rolling finger pressure along the tape to ensure wrinkle-free
attachment. Light rolling finger pressure was then applied to the sample from the first piece of tape across to the second, to ensure attachment along both edges without distorting the texture. Low pressure nitrogen gas was used to remove surface contaminants and debris. The mounted texture was placed in the center of the measurement stage under the 405 nm laser source. A 5x objective lens was used for magnification with no additional zoom factor. The upper and lower (z-direction) focal points were set using the microscope’s confocal optical system. The brightness was set automatically. Measurement pitch (step height) was set to 20 μm for each texture; the number of steps of z-direction height measurement varied with each sample based on the upper and lower focal points. The planar area captured with each scan was a 3x3 stitched composite of approximate linear dimensions 7.17 mm x 7.16 mm. Two measurements were made for each sample in different areas of the material. If necessary, the resulting profiles were rotated to align with the scanning direction of the texture as mounted on the drum. Welch’s method was used to estimate power spectra along the scanning direction, using each scan line as a separate window. Our method of characterizing a texture’s surface profile is similar to one previously employed (Bergmann Tiest and Kappers 2006), but relies on laser microscope rather than a stylus and more than a single scan line.

Fingerprint digitization: Fingertips from the right index finger of each subject were obtained using a SecuGen Hamster IV fingerprint scanner (SecuGen Corp., 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 10x resolution using cubic spline interpolation, 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 males, 2 females, 18-31 years old) provided informed consent and participated in this study. On each trial, the subject was presented with one of 55 textures and produced a rating in proportion to its perceived roughness, where a rating of zero denoted a perfectly smooth surface. Each texture was presented once in each of 6 experimental blocks; ratings were normalized by the mean of each block and averaged, first within then across subjects. Ratings of roughness were highly consistent across subjects (inter-subject correlation: 0.91 ± 0.03, mean ± s.d.). All procedures were approved by the Institutional Review Board of the University of Chicago.

**Data analysis**

**Texture classification:** To determine if the vibrations generated by one surface can be distinguished from those generated by another, we attempted to classify textures based on 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 one of three metrics, see below) between the spectra of each texture in group A and those of all the textures in group B (yielding 55x55 = 3025 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 based on 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 (30D) 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 contribution, 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 based on their pair-wise distances, we used Matlab’s hierarchical clustering functions. First, we built an agglomerative hierarchical cluster tree, using the 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 which 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).
Conversion between spatial and temporal frequency: The frequency content of texture surface profiles is naturally expressed in spatial units (cycle length or spatial period in mm), while that of the recorded vibrations is expressed in temporal units (cycles/s or Hz). Conversion between these two measures depends on the scanning speed, such that

\[ f_t = \frac{v}{p_s}, \quad (1) \]

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

Characterizing the periodicity of textures: In order to split textures into a periodic and a non-periodic set, we devised a simple criterion of periodicity. The profilometric frequency spectrum of non-periodic 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. Using 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 non-periodic textures, we only included textures in the periodic set if the frequency of the spectral peak was higher than the lower-frequency cut-off 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: In order 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 frequency 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 Equation 1, $r_{\text{trans}}$ should be higher than $r_{\text{no-trans}}$. The degree to which a texture translated was then given by:

$$I_{\text{trans}} = \tanh\left(\left(\tanh^{-1}(r_{\text{trans}}) - \tanh^{-1}(r_{\text{no-trans}})\right)\right)$$

where $I_{\text{trans}}$ takes on a value of 1 if $r_{\text{trans}} >> r_{\text{no-trans}}$ and -1 if $r_{\text{no-trans}} >> r_{\text{trans}}$.

Results

We scanned 55 different textures at three different speeds across subjects' fingertip skin using a custom-made rotating drum stimulator and measured the vibrations elicited in the skin using a laser Doppler vibrometer (Figure 1A,B,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 differ in amplitude, periodicity, and frequency composition (Figure 1D). Vibrations ranged from highly periodic (velvet), to highly non-periodic (fleece), with many textures comprising both periodic and non-periodic 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 based on the vibrations they elicit in the fingertip skin, we implemented a classification algorithm (see Materials and Methods) that discriminates textures based on features extracted from the recorded skin oscillations at a given speed. We found that textures were poorly classified based on the amplitude of the elicited vibrations alone (white bars in Figure 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 (Serina et al. 1997; Pawluk and Howe 1999; Nakazawa et al. 2000; 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 using normalized power spectra) was highly informative as to texture identity, with classification accuracy reaching 93% at 120 mm/s (black bars in Figure 2). Classifying textures using both amplitude and frequency composition led to a negligible increment in performance (gray bars in Figure 2). We further observed that classification performance improved slightly with increased speed, probably due
to higher vibratory power and thus higher signal to noise ratio at those speeds. Furthermore, the distance matrix exhibited some interpretable structure (Figure 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 based on the skin vibrations they elicit, we next determined 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 using 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 zero ($r = -0.07$ 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 will hard ones, 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 non-periodic set, depending on whether the surface profile exhibited a dominant peak in the power spectrum (see examples in Figure 4 and the full set in Table 1). Periodic textures (Figure 4A,B) typically evoked dominant peaks in the vibrometric spectra that matched their spatial period as measured by profilometry (Figure 5A). The peaks in both spectra shifted depending on the scanning speed. The majority of the misaligned peaks in the vibratory spectra fell 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 later). Non-periodic textures did not exhibit dominant peaks in their profilometric power spectra (Figure 4C,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 non-periodic 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 non-periodic textures. We found that profilometric centroids were highly correlated with the vibrometric ones at all three speeds (Figure 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 non-periodic textures, explaining why even non-periodic textures are easily discriminable based on 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 Figure 4D), and the spectral centroids of the vibrations tend to cluster around those frequencies, rather than spanning the broader range of the profilometric centroids (Figure 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.

The effect of scanning speed on texture-elicited vibrations

As expected, the peak frequencies of the vibrations elicited by periodic textures shifted systematically towards higher frequencies with increases in scanning speed. While this effect has been described previously for periodic textures, it is not clear whether the same rule would hold for non-periodic textures (Bensmaia and Hollins 2003; Delhaye et al. 2012). To quantify how the frequency spectra of texture vibrations translate as a function of scanning speed, we developed an index (Equation 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 ± standard deviation, averaged across speeds) on this measure and non-periodic textures (e.g., sandpapers, fuzzy fabrics)
yielded nearly identical values (0.67 ± 0.19; two-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. Equation 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 (Figure 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 (Figure 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 Figures 4D and 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 co-varied with that subject’s fingerprint period. Indeed, we found that subjects with coarser fingerprints exhibited filters with peaks at lower frequencies than subjects with finer fingerprints, and that the observed filter peak spatial periods closely aligned with the values expected given each subject’s fingerprint period (Figure 6C,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; Bensmaia and Hollins 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 (correlation = -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 non-linear transformation of the spatio-temporal pattern of skin deformation (Sripati et al. 2006; Kim et al. 2010; Dong et al. 2012) 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 non-contact 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 do not only reflect 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 based on 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
based on 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 based on 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 (Connor et al. 1990; Connor and Johnson 1992; Blake et al. 1997), concluding that slowly-
adapting type I (SA1) and rapidly-adapting (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). Rather, 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 (Mountcastle et al. 1972; Mackevicius et al. 2012). 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 is 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 (Bensmaia and Hollins 2003; Bensmaia and Hollins 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). To better disentangle 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 which, at least on the finger, 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 all over
the finger and palm; 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
based on 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.

The role of fingerprints in texture perception

The role of fingerprints in tactile perception has been controversial. While 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 non-periodic 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 (Fagiani et al. 2011; Fagiani et al. 2012).

We found that our set of everyday textures elicited vibrations which contained frequencies
corresponding to a subject’s fingerprint geometry. Crucially, this was not only the case for non-periodic
textures (like sandpaper), but for most textures in our set, which spanned the range from non-periodic
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 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 (Cummins et al. 1941; Ohler and Cummins 1942; Acree 1999), 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 Smith 1994, e.g.).

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 (Hartmann et al. 2003; Bagdasarian et al. 2013), 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 (Jones et al. 2004; Arabzadeh et al. 2005), and part of this temporal structure is preserved in barrel cortex (Ewert et al. 2008).

Applications

In addition to their implication 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; Wiertlewski et al. 2011b; Romano and Kuchenbecker 2012). 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., Oddo et al. 2011; Fishel and Loeb 2012) for use in biomimetic neuroprostheses.

Acknowledgments

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References


Figure captions

**Figure 1.** A. Experimental set-up. B. Rotating drum stimulator. C. The finger is positioned comfortably and the nail is fixed to a finger holder to prevent movement and ensure comfort during recording sessions. D. Vibrations elicited when three textures were scanned across the skin at 80 mm/s. Top panels: skin position (displacements) over time. Bottom panels: spectrograms of position traces highlighting spectral power at different frequencies over time. Increased brightness indicates greater spectral power.

**Figure 2.** Classification accuracy over all textures using either the amplitude of the elicited vibrations (white bars), the normalized frequency spectrum (black bars), or both (grey bars) as a basis for classification. Results are shown for all three scanning speeds. Error bars denote the standard error of the mean across subjects. Chance performance is around 0.018 (as there are 55 textures in our set). While textures can easily be classified based on the frequency composition of the vibrations they elicit, the amplitude of the vibrations alone is only marginally informative about texture identity.

**Figure 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 Table 1 for full ordering). The white boxes highlight four texture sets, with examples from these sets shown to either side of the distance matrix. For each example, the image on the left shows a small patch of the texture's surface profile (5 x 5 mm), while the graph on the right shows the power spectral density of the elicited vibrations at 120 mm/s (orange) and that of the corresponding surface profile (black). Out 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.

**Figure 4.** A. Profilometry for three periodic textures. The white arrow indicates the scanning direction. Patches are approximately 5 x 5 mm in size. B. Power spectral densities (PSDs, shown on linear scale) for the textures shown in A as calculated from the profilometry (black lines, adjusted for scanning speed) or vibrometry (blue and orange lines) at speeds of 80 and 120 mm/s (left and right columns, 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 three non-periodic textures. D. PSDs calculated from profilometry (black) and vibrometry (blue and orange) for two 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.
Figure 5. A. Peak frequency in the surface profile versus peak frequency in the vibrations for all periodic textures at the three 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 non-periodic 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.

Figure 6. A. Average PSDs over all textures for the profilometry (dark) and vibrometry (colored) at the three different speeds. Arrows denote average fingerprint spatial period across all subjects at the three speeds. As can be seen, vibrations exhibit peaks that match the average fingerprint spatial period. B. Linear filter of the transformation from profilometric to vibrometric spectra (see 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 two 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) versus average fingerprint ridge distance for the corresponding subject. The dotted line denotes unity. As expected, denser fingerprints lead to higher peak frequencies.
Table 1. All 55 textures, ordered by perceived roughness from smooth to rough by row then column. Asterisks denote periodic textures (see 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. Numbers in superscript denote the texture order in the clustering analysis shown in Figure 3.

<table>
<thead>
<tr>
<th>Texture Description</th>
<th>Vendor/Manufacturer</th>
<th>Code</th>
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</thead>
<tbody>
<tr>
<td>Vinyl (20 gauge)</td>
<td>J</td>
<td>16</td>
</tr>
<tr>
<td>*Swimwear Lining (polyester/spandex)</td>
<td>J</td>
<td>46</td>
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<tr>
<td>*Sparkle Vinyl Back</td>
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