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Building a navigable fine texture design space

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***Abstract*—Friction modulation technology enables the creation of textural effects on flat haptic displays. However, an intuitive and manageably small design space for construction of such haptic textures remains an unfulfilled goal for user interface designers. In this paper, we explore perceptually relevant features of fine texture for use in texture construction and modification. Beginning with simple sinusoidal patterns of friction force that vary in frequency and amplitude, we define irregularity, essentially a variable amount of introduced noise, as a third building block of a texture pattern. We demonstrate using multidimensional scaling that all three parameters are scalable features perceptually distinct from each other. Additionally, participants' verbal descriptions of this 3-dimensional design space provide insight into their intuitive interpretation of the physical parameter changes.**

***Index Terms*—Surface Haptics, Friction Modulation, Texture, MDS.**

I. Introduction

TOUCHSCREENS are an essential window through which we explore and control our environments, yet they provide little or no actual touch feedback to their users. Friction modulation technology allows us to build touchscreens that can provide a wide variety of tactile effects by inducing variable lateral forces on the fingertip, either via ultrasonic friction modulation [1]–[3] or electroadhesion [4], [5]. One effect particularly well suited to these friction-modulating haptic displays is texture simulation, as texture is already a highly salient characteristic of flat surfaces. Of particular interest are fine textures, which elicit primarily higher frequency vibrations on the skin during active touch.

A wide range of textures available for display could facilitate communication by helping users navigate a screen or locate icons and buttons. Haptic texture can also facilitate emotive communication, for example by simulating the sensation of stroking a friend's arm or petting a favorite dog's fur. However, building satisfying textures for these purposes is nontrivial: how can we provide texture designers a library of differentiable textures, as well as usable tools to enhance and modify them? An ongoing goal is to identify characteristics of variable friction fine textures that can be both mathematically and perceptually scaled. Such continuously variable features can then serve as our tools of enhancement and modification.

A. *Defining a texture workspace*

Texture in any sensory modality, whether visual, auditory, or tactile, encompasses a wide range of length scales. These range from larger coarse features to very fine micro details, and not all of these scales should necessarily be designed and modified using the same parameter sets. Tactile texture specifically consists of both macro texture, detected as larger distinct features on the surface, and micro (or "fine") texture, which is detectable primarily through vibrations produced on the skin during active exploration. David Katz referred to this macro versus micro duality almost a century ago in his book "The World of Touch", an early and hugely significant introduction to tactile perception [6]. Later work revealed that the somatosensory system has disparate methods of detecting the two types of texture via different types of mechanoreceptors, which are responsible for either lower or higher frequency content [7]. Pacinian Corpuscle (PC) mechanoreceptors, sensitive to temporal vibrations approximately 50 Hz or higher, are primarily responsible for our ability to discriminate fine textures and rate their roughness [8], [9]. Scanning over spatially distributed micro surface features generates these temporal vibrations on the skin responsible for fine texture perception, and we can describe fine texture as consisting of either small spatial length scales or the higher frequency vibrations they elicit.

In this work we focus on textures composed of finer length scale vibrations, applied using variable friction displays. Several studies have found that at length scales under 1 mm, the relative phases of frequency components do not affect texture discrimination [10], [11]. This demonstrates that for fine texture, quite a bit of information is lost or combined by the somatosensory system, making these textures ripe for reduced representation. A primary inspiration for our approach to texture design and modification is the "Tactile Paintbrush" approach by Meyer et. al. [12], which posited that any friction-varying pattern composed of length scales of 1 mm^{-1} or finer could be entirely described by its magnitude spectrum, as well as a statistical characterization of how those magnitudes varied over time or space. This results in vastly fewer parameters to describe a given texture than an entire mapping of all friction values for the length of the texture, but remains an unwieldy amount (200+ numbers to adjust) for a texture designer.

Subsequent work suggests that a detailed description of a fine texture's spectrum is probably still an over- parameterization: several studies of textures or vibrations composed of 2 frequency components demonstrate that they are quite perceptually similar to those composed of only one [13], [14]. Here, a single perceived frequency, or pitch, might be a characteristic of a more complicated spectrum. What other simplified characteristics can we extract from a texture's spectrum that summarize its most salient perceptual qualities? We can look for relevant characteristics using multidimensional scaling, which provides a means to visualize how various mathematical

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parameters of a texture are reflected in a perceptual space.

B. Perceptual dimensions of natural textures

Multidimensional Scaling (MDS) is an analysis technique that visualizes perceived dissimilarities between stimuli as distances in a perceptual space. In perceptual space, we can look for clusters of similar-feeling stimuli, or how physical changes to those stimuli result in perceptual changes. We can also determine how many dimensions account for perceptual differences by looking at the amount of stress imposed when mapping all the dissimilarities into an n-dimensional space. This analysis technique has been applied to multiple sensory modalities, such as taste and vision, to reveal relationships between a wide array of consumer products and psychophysical stimuli, and has been used extensively in haptic texture perception since the 1990s.

Many of the earlier studies looking at the perceptual space of texture queried the differences amongst real samples, such as wood, sandpaper, or different types of cloth. One of the first, by Hollins et. al. [15], found a 3 dimensional space with perceptual axes of rough/smooth, hard/soft, sticky/slippery. This dimensionality and these types of axes are commonly found in many other studies as well, along with alternative axes such as moist/dry and cold/warm; see [16] for a thorough overview of work on textural perceptual dimensions through 2013. Differences in primary axes found may be due to particular textures chosen to be included in a given set.

In addition to finding perceptual axes, we often wish to know what physical properties underlie a given texture's position along a perceptual axis. As demonstrated by Bergmann Tiest and Kappers [17], gradients pointing in the direction of greatest change of measured parameters of the textures, such as surface roughness or average kinetic friction, can be mapped onto the perceptual space. Work looking at the dimensionality of real textures continues to this day; for example, work by Vardar et al [18] suggests that the three dimensions originally found by Hollins may be related to physical measurements of spectral features such as power, centroid, and DC friction levels. Further research is needed to determine conclusively the physical properties that underpin perceptual dimensions.

C. Perceptual dimensions of textures for haptic displays

With the advent of more sophisticated haptic displays, researchers have been able to extend the range of possible textures to artificial ones composed of applied forces and vibrations. An advantage of artificial textures is the opportunity to actually choose and precisely adjust physical parameters, beyond simply measuring their values. On the other hand, it is by no means clear how best to select parameters or synthesize these textures.

One method of creating distinguishable textures for haptic displays is to play back recordings of real textures. Such recordings generally consist of measured lateral forces or accelerations on a finger or probe when scanning a real texture, while playback occurs via modulations in friction force or vibrations on a haptic display. Elements of the recorded signal can be analyzed and used in a reconstituted virtual texture [19], or the recorded signal can be played back as a function of measured scanning velocity and pressing force [20]. In one implementation of playback, researchers explored perception of real textures and recordings, and demonstrated that real textures were generally closer in perceptual space to their corresponding recording than to other recordings or simple periodic virtual textures [21]. Ultimately, playback can approximate the wide diversity of real world textures, but relies on a large library of recordings that does not immediately lend itself to novel virtual texture construction or modification. Recent work by Hassan et. al. sought to bridge this gap [22]. Using 25 real textures mapped into perceptual space, they interpolated weighted recordings of those textures to generate new textures that would lie at a desired spot in the perceptual space.

An alternative approach to new texture construction is building from the ground up, independent of real texture recordings, and observing which adjustable design parameters result in larger perceptual differences. To date, these designs generally consist of a modest repertoire of features, such as a few force values or frequency components. For example, one study working with an electroadhesive screen generated a coarse texture set consisting of only two friction levels [23]. The authors varied the overall friction difference, as well as the line width and spacing for different tessellated patterns, and found that parameters related to intensity, such as line thickness and friction levels, dominated perception. Either pattern shape or density (i.e. frequency of line spacing), depending on overall intensity, was also significant. Similarly, a study applying pulses of force via a stylus varied the amplitude and timing of pulses, and found that amplitude of pulses mapped very strongly onto their 2D perceptual space, while frequency and different rhythm patterns were somewhat entwined along the same axis [24]. Another group looked for continuous changes in engineering parameters reflected in MDS space [25]. Their texture set, displayed on an ultrasonic friction modulating screen, consisted of pairs of harmonic frequency components. Textures were best fit by two dimensions and varied by overall amplitude, fundamental frequency value, and inter-frequency spacing.

We cannot automatically assume these artificially constructed textures will have the same perceptual axes as real textures or their recordings. Real textures have a rich spectral complexity in applied force that may not be perceptually reproducible in simpler periodic patterns. Do artificial textures' limited number of variable features result in a different set of salient perceptual axes? Dariosecq et.al. found that generally axes were preserved, comparing verbal descriptions of sinusoidal and square wave friction-modulated patterns to those of real textures in previous perceptual studies [26]. Analyzing the words participants used to describe different patterns using factor analysis, they found that the rough/smooth axis from real textures also appeared for friction modulated ones, dependent on waveform amplitude and to a lesser degree on spatial frequency.

D. Parameter choice for texture workspace

Previous research exploring the perceptual dimensionality of artificial textures has generally used frequency of regularly spaced features as a controlled parameter, albeit in a variety of forms, i.e. pulse timing, tessellated pattern size, or period of sinusoidal and square waves. Intensity is also a reoccurring parameter, most often as the strength of pulses or overall friction range. Intensity is also related to wave form; square waves will feel more intense than sinusoidal due to the introduction of harmonics, which add to the power of the signal. Overall, frequency and intensity are clearly salient characteristics, and as features of a sinusoid (where intensity translates as amplitude) they constitute the simplest form of spectral information. Therefore, we also chose these two characteristics of a sinusoidal variation in friction as our first two parameters.

It is worth noting that frequency and amplitude in the fine texture regime are not necessarily perceptually orthogonal. A better term for frequency perception would be pitch, the perceived frequency of a signal that is dependent both on actual frequency and amplitude. Georg von Bekesy, a Nobel Prize winning scientist best known for his early work in audition and pitch perception via the cochlea, also wrote extensively about tactile pitch perception, noting that perceived pitch is inversely related to amplitude [27]. Studies looking at only frequency and amplitude as parameters often first construct iso-amplitude functions of frequency in order to keep the two features independent of each other, e.g. in [14]. While we have not done this in the following study, it will be interesting to observe the degree of independence additional parameters have with amplitude and frequency.

While 200 individually recorded frequency component values is almost certainly an over-parameterization of the perceptual space, psychophysical work suggests that merely a single sinusoid is a gross under-parameterization. [28] demonstrates that high frequency vibrations are not detected simply as intensity coding; rather, at least some level of spectral complexity can be detected. How can we go about capturing the most perceptible aspects of spectral complexity with just a few parameters? Previous groups have taken a variety of approaches in the above MDS studies, such as changing rhythmicity, which could be thought of as changing spectral information over time, or adding a second frequency component. Changing waveform type can also be thought of as adding more frequency components in the form of harmonics.

Informal experimentation suggests that white noise, even bandpassed to only higher frequencies in the fine texture regime, feels significantly different from a pure sinusoidal vibration. This stark difference makes “added noise” a potential candidate for a scalable feature of fine texture. Recently, different types of added noise have been tested as features to continuously increase for textures that can provide directional cues [29]. These methods, termed either “injected zero drops” or “added white noise” involve injecting more or less spectral noise to an existing pattern such as a sinusoid. In this paper, we explore varying the breadth of spectral noise, while leaving the centroid relatively unchanged. By filtering white noise with a variable width filter, we can continuously scale from a single sinusoid to broad noise. We will refer to this characteristic as added “irregularity”. We hope to understand whether this characteristic also scales continuously in perceptual space, and whether it is perceived independently of amplitude and frequency.

E. Empirical Study

Amplitude and frequency of sinusoidal textures are well established as perceptually relevant features. In this work, we present a third continuously variable texture feature, irregularity. We want to check whether it is perceptually distinct from the others, and observe how people describe its presence.

II. Methods

A. Set Construction

We constructed a set of variable friction textures that differed in a sinusoidal center frequency f_0, amplitude A, and ”irregularity” R. This latter quality refers to the width of the spectral content around f_0. Here, we directly specify spectral width via the Q-factor of a band pass filter applied to white noise. A larger Q-factor results in a narrower filter, and therefore less irregularity and an increasingly ”pure” sine wave. The filter used for texture construction, shown in equation 1, uses a Q-factor that inversely depends on R and a peak spectral magnitude located at f_0 as specified in equations 2 and 3. The sampling frequency f_s was 100 kHz.

$$H(z) = \frac{\frac{\sin w_0}{2Q} - \frac{\sin w_0}{2Q} z^{-2}}{(1+\frac{\sin w_0}{2Q}) - (2\cos w_0)z^{-1} + (1-\frac{\sin w_0}{2Q})z^{-2}} \quad (1)$$

$$Q = \frac{1}{R} \quad (2)$$

$$w_0 = \frac{2\pi f_0}{f_s} \quad (3)$$

Each parameter, listed in Table I, had three logarithmically scaled values; a minimum of three values was required to investigate whether the parameters scaled monotonically in perceptual space, while more than three values would result in an increasingly unwieldy number of parameter combinations. All three center frequency values are above 150 Hz, well within the range of PC mechanoreceptor sensitivity and therefore reasonably classified as fine texture vibrations. Amplitude and irregularity values were spaced far enough to be easily distinguishable and take advantage of the range of the display.

TABLE I
Parameter Values

Center frequency (Hz)	amplitude (normalized)	irregularity (1/Q-factor)
150	0.30	0.067
260	0.55	0.34
450	1.0	1.67

Narrower band filtering initially resulted in large low frequency fluctuations in amplitude, as illustrated in Fig. 1(b).

These fluctuations are problematic, as they perceptually overwhelm the finer frequency components and result primarily in the sensation of very low frequency throbbing. Additionally, they have a large impact on overall maximum amplitude, swamping any contribution of a gain term. In order to correct for these deleterious side effects, each filtered signal was divided by its envelope, calculated using the Hilbert transform via the envelope function in MATLAB 2019. The effect of this transformation on the signal in both the time domain and in frequency space is demonstrated in Fig. 1(c). Textures demonstrating the three different irregularity values for a 260 Hz center frequency and the maximum amplitude are shown in Fig. 2.

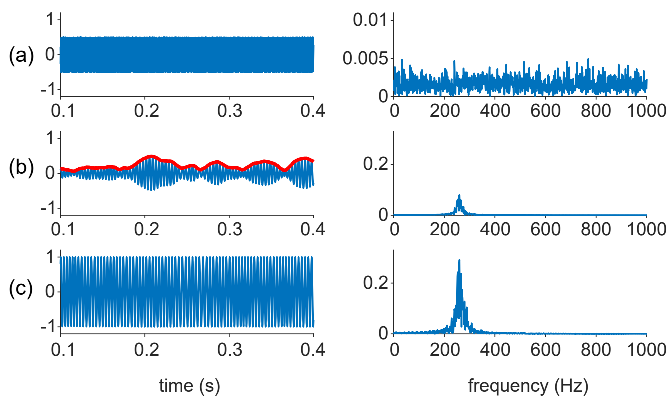

Fig. 1. Demonstration of texture construction. Time domain signals are shown on in the left column for (a) broadband white noise, (b) filtered white noise and its envelope indicated in red, and (c) the filtered noise divided by its envelope. Corresponding magnitude spectra are on the right for reference.

Dividing filtered signals by their envelope results in an maximum amplitude of one in the time domain. We then scale the signal down to 55% or 30% of its original amount for the smaller amplitude parameter values. Finally, we excluded textures with the highest frequency and lowest amplitude value from the set, as they were perceptually weak enough to be difficult to detect by the experimenters. All other amplitude and center frequency values had three variations of filter width, resulting in 24 textures total.

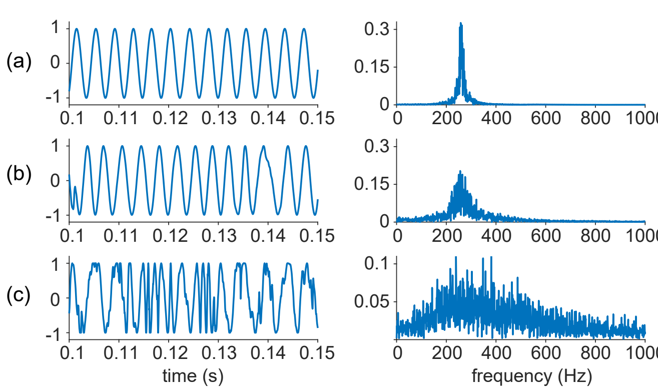

Fig. 2. Time domain signals and their magnitude spectra for three different irregularity values, all with 260 Hz center frequency and amplitude of 1.

B. Apparatus

Variable friction textures are displayed on a commercially available 3M screen, custom cut into a circular disk for use on a turntable. Controlled current was applied directly to the conductive ITO layer of the screen via a wire bonded to the side of the cut glass with silver epoxy; device design and specifications for this particular apparatus are detailed in Shultz's 2018 paper on applying electroadhesive friction modulation [4]. The turntable rotates continuously under the finger, ensuring a consistent scanning velocity across all users and negating the need to change or disrupt swipe direction. Users rest their right index fingernail against a guide block which ensures a consistent finger placement at an angle of incidence 45 degrees to the surface, approximately 60 mm from the center of the disk. The turntable rotates 33 revolutions per minute, resulting in a scanning velocity of approximately 200 mm/s perpendicular to finger orientation. See Fig. 3 for an image of the setup.

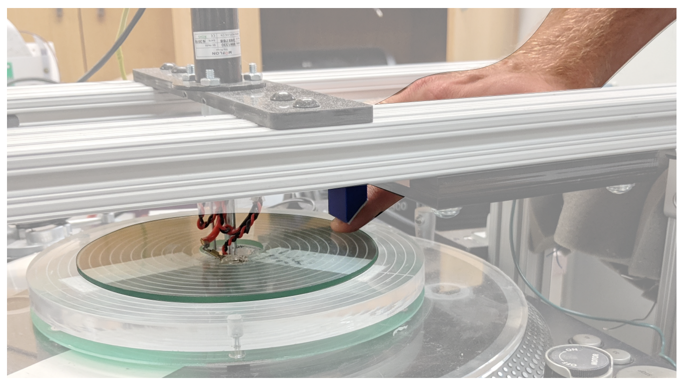

Fig. 3. Image of friction-modulating display. The hand, guide block, and disk-shaped 3M screen are highlighted.

Textures in the above set design have a unitless amplitude of up to 1 and are centered on 0. In application, our display can only increase friction, resulting in textures composed of a modulated friction force which will always be positive and bounded by the achievable friction range of a given display. For this apparatus, we control force via amplitude modulation of a 20 kHz carrier current, a method first introduced by Meyer et. al. in 2014 [30]. Schultz et. al. [4] further characterized this method, demonstrating that the 3M screen used in this apparatus has a relatively linear relationship between applied current envelope and resultant friction force in the range of 1-5 mA. Therefore, the 24 textures in this experiment are scaled for use as a modulation envelope spanning a maximum range of 1-5 mA and centered on 3 mA to ensure consistent average friction across the set.

While we assume a linear relationship between commanded signal and applied friction force, their relationship to actual finger velocity for this setup has not been explored in depth. In order to understand how our applied friction force translates to movement of the skin, we performed a frequency sweep from 10 to 1000 Hz for a constant sinusoidal current envelope bounded by 1 to 5 mA. A Polytec LDV (IVS-500) measured oscillating velocity of the side of the finger a few millimeters above surface contact, and perpendicular to finger sliding

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direction. Fig. 4 shows the frequency response collected from the lead author's finger. For frequencies between 25 and 250 Hz, we can see that the response is fairly flat; over this range, changing the frequency of force oscillation will not greatly affect the maximum skin velocity. However, this velocity begins to roll off above approximately 250 Hz, and higher frequency vibrations on the skin decrease in amplitude. Previous device characterization [4] demonstrates no attenuation in applied force over this range; therefore, this behavior is likely a result of mechanical damping by the viscoelastic fingertip tissue.

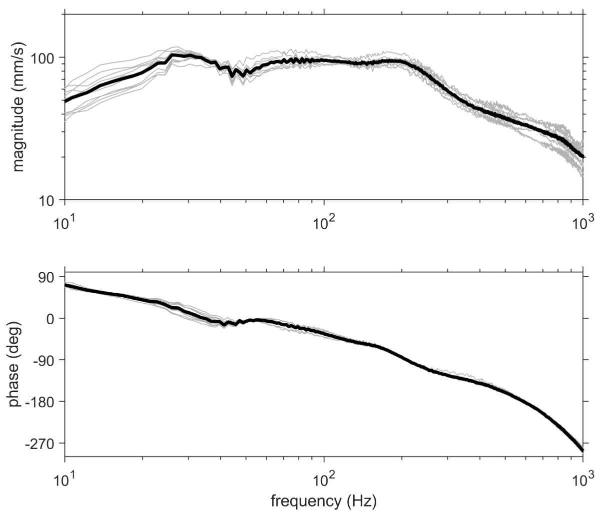

Fig. 4. Bode plot for commanded friction vs LDV velocity measurements. 10 trials are shown in grayscale, while the average result is in black.

C. Psychophysical Procedure

17 people (one left handed) ranging in age 18-35 (median age 26) participated in this study. This work was approved by the Northwestern Institutional Review Board, and all participants were reimbursed for their time. When interacting with the apparatus, participants placed their right index finger on the display surface and actuated texture playback with their left hand on a separate tablet displaying the user interface shown in Fig. 5. They also listened to pink noise on noise cancelling headphones during texture playback in order to ensure that any audio effects coming off their finger did not influence their haptic perception. Texture order in the user interface was randomly scrambled between participants to ensure that button location did not affect grouping behavior across the population.

At the outset of the experiment, participants were asked to first feel the entire set of 24 textures. This helped them become comfortable with the experimental setup and ensured that they were acquainted with entire range of textures. During this time, any remaining questions regarding the user interface could be addressed, as well as any ergonomic changes such as chair height or arm support.

Following the training period, participants began round 1 of the experiment. They were instructed to assign all textures to groups, so that textures within a group were similar to one another, and textures in different groups more dissimilar. They could choose the number of groups that they felt was necessary, up to a maximum of 12 separate groups. A given texture was assigned to a group by first selecting and playing that texture from the left side of the GUI, and then selecting a group assignment from the right side. Once the participant was satisfied with their group assignments, they alerted the experimenter that they were finished.

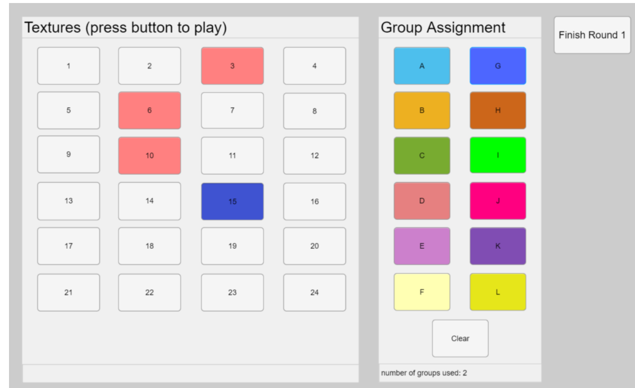

Fig. 5. User interface for participant trials. In this example, textures 3, 6, and 10 are assigned to group D, texture 15 is assigned to group G, and the rest of the textures have yet to be assigned.

Throughout the experiment, participants could play any texture as many times as desired and reassign it to different groups for the duration of the experimental round. Although the 24-texture set is too large to simultaneously hold in memory, participants often compared each texture to many others when determining a particular group assignment, and this ability to perform unlimited pairwise comparisons allowed people to track and sort the entire set without relying too heavily on memory alone.

A single round of grouping is somewhat disadvantaged in that for a given person, we cannot extract any gradation of similarities between textures [16], [31]. Therefore, once all textures were assigned to an initial group, participants proceeded to round 2 where they were asked to reduce the number of groups by roughly half by combining more similar groups. In a final third round, they reduced the number of groups yet again. At the end of round 3, they gave each of their remaining groups a name or phrase to describe the common characteristic of textures within each group. After observing group names that encompassed multiple characteristics for the first few experiments, group names were also collected for participants #7-17 following the second round.

III. Results

A. Multidimensional Scaling

Three rounds of increasingly coarse grouping assignments were used to construct a matrix tabulating the perceived similarities of all textures to each other. Using a ranked point assignment similar to that in [31], textures grouped together in earlier experimental rounds received more points than those grouped subsequently, resulting in zero (never grouped) to three (grouped in the first round) points from each participant

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for each pairing. Points were summed across all participants, resulting in the similarity matrix shown in Fig. 6. Two textures could have a maximum similarity of 72, with 24 participants and 3 possible points, if always grouped on the first round, and minimum similarity of zero if they were never grouped by anyone. The similarity relationships in this matrix were then visualized as distances using Multidimensional Scaling (MDS).

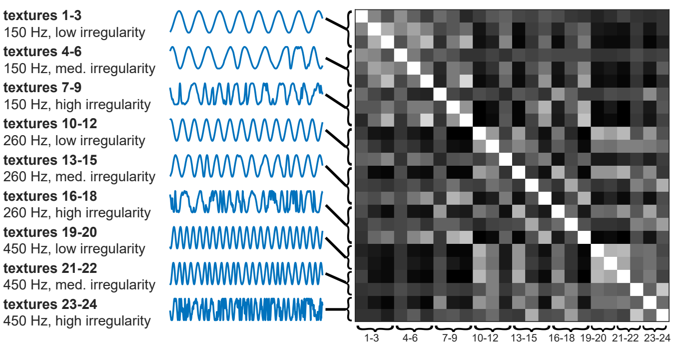

Fig. 6. The gray scale similarity matrix for all 24 textures. Black corresponds with lowest similarity, and white with perfect similarity across all participants. Textures 1-18 have three different amplitude values for each example shown, increasing in sequential order, while the lowest amplitudes are omitted for the 450 Hz textures.

A nonmetric MDS analysis was performed using Krushal's stress criterion 1, where distances in MDS space decrease monotonically with increased similarity. Determining the appropriate number of dimensions for this space is often nontrivial; fully satisfying a stress criterion depends not only on how many factors are actually responsible for perception, but also on any noise in participant responses. In other words, unless there are as many dimensions as there are stimuli, there will always be some stress (i.e. warping) of stimuli locations when fitting perceived similarities to a limited-dimension space. A common method for distinguishing relevant dimensions from participant-related noise is to look for a characteristic "knee" in the stress value. This abrupt flattening of the stress for increasing numbers of dimensions indicates that further dimensions may be due primarily to noise in the data, and would give diminishing returns with regards to explaining meaningful differences in similarities. However, real data summarized over many participants often fails to show a clearly discernible knee in the stress values. In absence of a clear knee, another commonly used metric is to simply choose a maximum acceptable stress cutoff, commonly at 0.15 [32]. Our measured stress has a slight knee at three dimensions, shown in Fig. 7 (a), although this bend is far from dramatic. Since the knee also occurs below a 0.15 stress value, we selected three as the number of dimensions for use in further analysis. The slightly spherical nature of the 3D solution in Fig. 7 (b) suggests that this amount may not perfectly encompass the entirety of perceived dimensions [33], but adding further dimensions becomes prohibitive to visualization and interpretation.

We can observe how the engineering parameters, i.e. frequency, amplitude, and irregularity, map into this MDS space. Fig. 8 shows the same perceptual space in all three plots, but with textures shaded differently to reflect the three values of each parameter. Corresponding vectors for each parameter are also included. These vectors, calculated in equation 4, align with the direction of greatest change for a given parameter, and their length corresponds with the influence that parameter has on perception; see [17] for a full derivation.

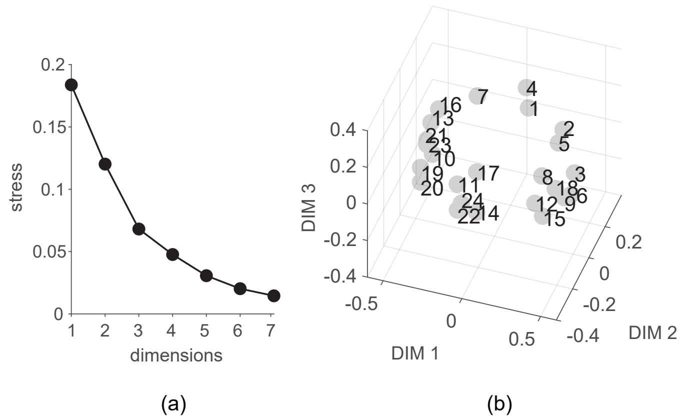

Fig. 7. Results for MDS. (a) Scree plot, with elbow observed at 3 dimensions. (b) 3-dimensional perceptual space with labeled textures.

$$\vec{p} = \frac{\sum q_i \vec{x}_i}{\sum q_i^2} \tag{4}$$

Here, a given vector $\vec{p}$ for a particular parameter q depends on each ith texture's parameter value q_i and position in MDS space $\vec{x}_i$, summed over all textures. The first two plots in Fig. 8 are oriented perpendicular to the irregularity vector and so show only the frequency and amplitude vectors, while the third plot is rotated to show the ordered distribution of irregularity values.

B. Perceived Parameters

Angles between each pair of the three engineering parameter vectors in MDS perceptual space are reported in Table II. While no pair of vectors is precisely orthogonal, as would be expected from perceptual independence, they are far from co-linear, and collectively, the three engineering vectors cover the three-dimensional MDS space. These results indicated that the engineering parameters are perceptually distinguishable but do not precisely align with the dimensions underlying texture-similarity judgments.

TABLE II
ANGLES BETWEEN ENGINEERING PARAMETER VECTORS

	angle
frequency-amplitude	128°
amplitude-irregularity	74°
irregularity-frequency	109°

While the distances between stimuli have clear meaning in MDS space, the rotational orientation of the entire set of stimuli does not necessarily. However, the longest section of space, corresponding with the most perceived difference,

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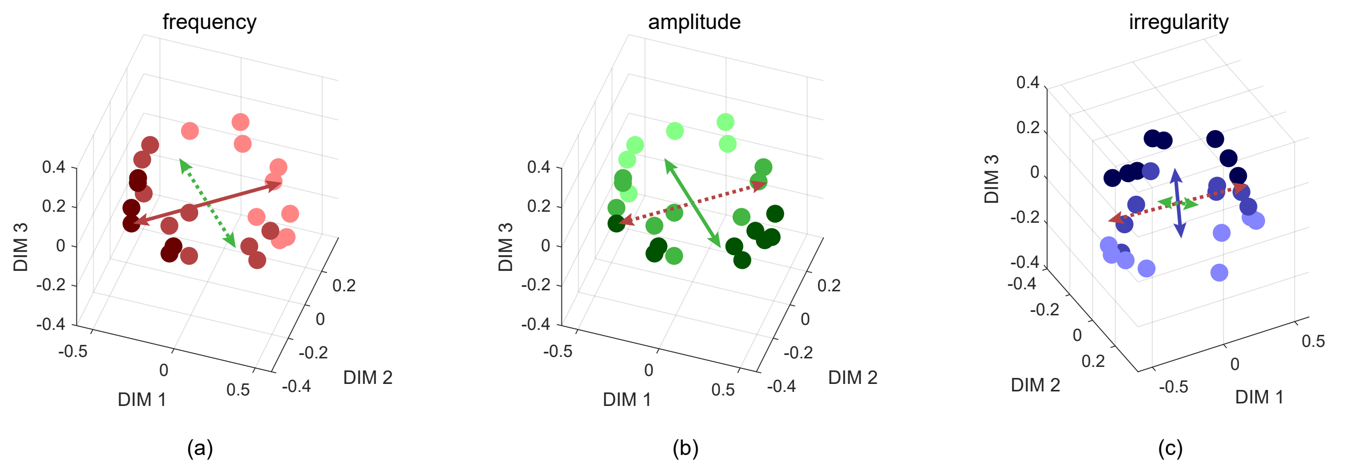

Fig. 8. Projections of the 24 textures located in 3-dimensional MDS space, plotted separately to highlight effects of changing frequency, amplitude, and irregularity. Each plot demonstrates the ordered gradation of lowest parameter values (lightest marker shade) to highest value (darkest marker shade) for the respective parameter. Color coded vectors in each plot, calculated from equation 4, indicate the direction of gradient change for each parameter. Plots (a) and (b) are projected perpendicular to the irregularity vector axis, while (c) is rotated to show the irregularity gradient.

is oriented along dimension one. This invites speculation as to whether the MDS dimensions, particularly dimension one, are a truer representation of the "perceived" parameters, in contrast with the engineering parameters. Table III shows the correlations for the MDS dimensions with each engineering parameter; stronger relationships are highlighted in bold. All dimensions are somewhat correlated with all three parameters, although to differing degrees. Dimension one appears to represent an inverse relationship between frequency and amplitude, with very little correlation with irregularity, while Dimension two is primarily correlated with irregularity. Dimension three depends most strongly on irregularity and amplitude.

TABLE III
CORRELATIONS BETWEEN PARAMETERS AND MDS DIMENSIONS

	frequency	amplitude	irregularity
Dim 1	**-0.669**	**0.480**	-0.121
Dim 2	-0.447	-0.420	**-0.534**
Dim 3	-0.305	**-0.562**	**0.644**

C. Semantic Analysis

We also analyzed peoples' qualitative interpretation of our three engineering parameters by observing how they described textures across different areas of MDS space. We hoped to determine whether our chosen parameters were easily identifiable or confusingly abstract, and to search for more intuitive names for use in texture design.

We initially asked participants to assign descriptive names to their groups of textures in the final round of grouping, with either a single word or as short a phrase as possible. However, it quickly became apparent that this final grouping stage was too late to differentiate all perceived textural traits; people were assigning names to groups with long phrases that often encompassed several features, such as "rough/scratchy/low/deep" or "strong or bass or medium freq + high amplitude". Therefore, we asked the final 11 participants to name their groups following the second round of grouping. This resulted in names encompassing one to two traits, such as "chirpy" or "heavy, low-pitched." All group names from the second round of grouping are distributed in Fig. 9, where each name is shown at the average location of all the textures that were members of that group. For example, participant #11 assigned the name "chirpy" to one of their groups containing three textures, and the locations of these three textures in MDS space were averaged to produce the location of the word "chirpy" on the plots in Fig. 9.

Many of the group names along the frequency and amplitude vectors are directly related to these engineering parameters, including "strongest, lower freq[uency]" and "weakest, higher freq[uency]" highlighted in bold in Fig. 9 (a). Phrases such as "loud", "jackhammer" and "feather", while slightly more abstract, still suggest a variety of perceived amplitudes. Similarly, multiple references to pitch and frequency indicate that frequency was a particularly salient parameter.

In contrast, a clear relationship between the irregularity axis and group names was not readily apparent. Participants appeared to be much more creative but less consistent in their group descriptions, as highlighted again in bold in Fig. 9 (b). Groups of textures on the lower end of irregularity have names including "sticky patches" and "bumblebee", while those with more irregularity have names such as "tickle" and "chirpy".

IV. DISCUSSION

The primary goal of this work was to determine distinguishable building blocks of fine texture that could be independently adjusted and continuously scaled. Previous studies exploring construction and modification of virtual textures either relied on large libraries of real texture recordings [21], [22], or only explored deterministic periodic texture patterns with a limited number of frequency components and amplitudes [23]–[25]. By building textures with a given irregularity value in addition to frequency and amplitude, we have introduced a new differentiable feature for fine texture design while still

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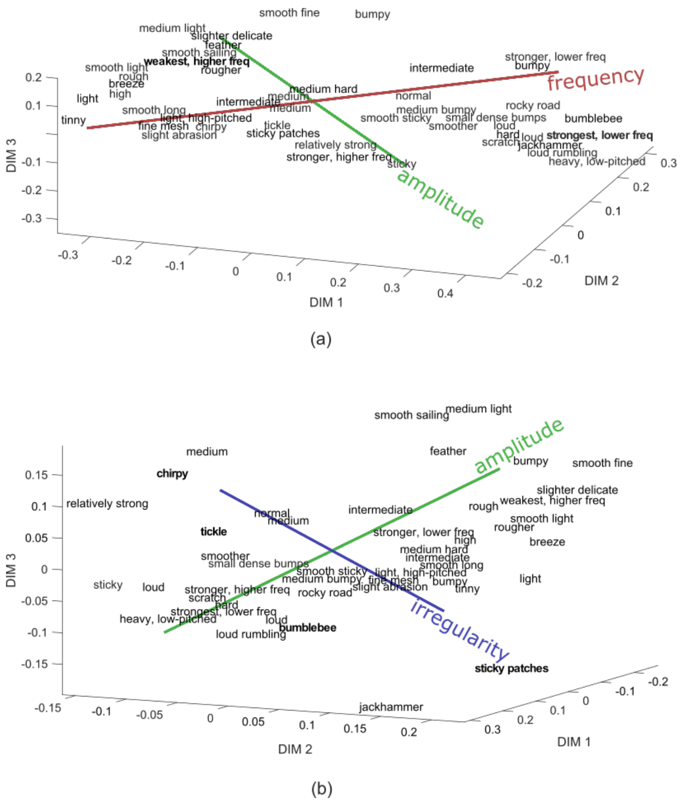

Fig. 9. Phrases describing traits of texture groups, shown in projections of MDS space along (a) the irregularity vector and (b) the frequency vector. Each plotted phrase was chosen by a study participant to describe a set of grouped textures, and is shown at the mean location of those textures in MDS space.

maintaining a small parameter set and simple construction method.

The three engineering parameters, frequency, amplitude, and irregularity, are all well represented in MDS space, as indicated by the corresponding vectors calculated in equation 3. In addition, the angles between vector pairs indicate substantial independence, if not orthogonality. These results suggest that the engineering parameters could be good candidates for adjustable controls for texture design. The relative length of these vectors, as computed from the distribution of the textures along them, indicates their importance to perceived textural similarity, which could be used to scale the controls to maximize salient contributions.

Irregularity, as defined in this work, is essentially a scalable introduction of noise. There are alternative methods of introducing increasing amounts of noise, such as increasing the amplitude of additive pink or white noise atop other signal elements, that merit further study, but this particular method has provided an adequately differentiable feature from the amplitude and frequency of a fine texture. However, descriptive group names suggest that people do not innately have the vocabulary to describe this type of parameter change. Creative names such as “bumblebee” and “chirpy” hint at substantive experiences, but are not easily interpreted by other readers. A better approach to understanding the qualitative interpretation of this parameter may be to provide future study participants with a predefined vocabulary list for noise-like parameters from which they can select or rank terms.

While clearly differentiated in the MDS solution, the parameter vectors are not aligned with the three emergent perceptual dimensions. This is not necessarily an indication that the actual perceived features are different from the engineered ones, as MDS maps out inter-stimulus distances and not orientation. However, the most differentiated stretch of the MDS space, oriented along dimension one, appears to be a perceptual conflation of frequency and amplitude. Table III shows that this dimension has an inverse dependence on frequency and amplitude, and almost no correlation with irregularity. In Fig. 9, we can see that participants’ group names also refer to combinations of these parameters with terms along dimension one such as “low-pitched” and “high-pitched”. Pitch, i.e. perceived tactile frequency, specifically has been shown to depend on an inverse relationship between frequency and amplitude [27], and can be identified even when there are multiple frequency components present [13], [14].

The apparatus used for these experiments enabled uniformity of scanning velocity across all participants. This allowed for precise control of frequency content often present in fundamental neuroscience [9], yet does not simulate real world textural interactions. For future work, allowing participants to actively control and modulate their scanning speed could provide further insight into how they explore and perceive features such as irregularity. While we did not monitor pressing force at all, it is reasonable to assume that this force remained relatively constant across textures for a given participant; once participants were situated in the experimental setup, they maintained a constant finger placement by bracing against the guide block. Although pressing force has been shown to influence perceived roughness of textures on electrostatic displays [34], this would have limited impact on inter-texture comparisons for a given participant using a constant pressing force.

Future work is needed to determine whether and how well people can use the engineering parameters in this study to adjust textural features. Examples of such adjustments include intentionally enhancing a chosen trait, or trying to perceptually match another texture using a combination of all parameter settings. Would users be able to navigate a 3-dimensional design space faster or more accurately with the original engineering parameters, or would the emergent MDS dimensions provide more intuitive control? Adjustment ”knobs” representing emergent dimensions might consist of linear combinations of the engineering parameters, or other functions of the parameters that represent established characteristics such as tactile pitch. An optimal step size for such knobs also remains to be explored; in particular, the perceptual resolution of irregularity values is unknown, and would inform a useful increment of parameter value increase or decrease for texture modification.

Characteristics such as temperature, deformability, and pile all contribute to the rich breadth of fine textures we can distinguish in the real world. However, even within the limitations of a screen that can only modulate friction forces, it is conceivable that there are more independent textural characteristics not addressed by our three engineering parameters. For this reason, future experiments should examine whether there are friction modulated fine textures that cannot be perceptually matched by our texture generation scheme. This would take us one step further toward understanding the full gamut of friction modulated textures, and how our 3-parameter space fits within it.

V. Conclusion

We constructed a 3-dimensional fine texture design space for variable friction haptic surface displays. Engineering design parameters included frequency and amplitude of sinusoidal changes in friction, as well as an irregularity term proportional to width of spectral noise. Via multidimensional scaling, these parameters show up in perceptual space relatively orthogonal to each other. Perceptual dimensions appear to be combinations of the engineering parameters, with the primary dimension an inverse relationship between frequency and amplitude, the second dimension most dependent on irregularity, and the third a function of all three parameters. Analysis of texture group names given by participants suggest that people have no problem identifying pitch-like and volume-like features, but struggle to cohesively name injections of irregularity.

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